

# A Beta Way: A Tutorial For Using Beta Regression in Psychological Research

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## Abstract

Rates, percentages, and proportions are common outcomes in psychology and the social sciences. These outcomes are often analyzed using models that assume normality, but this practice overlooks important features of the data, such as their natural bounds at 0 and 1. As a result, estimates can become distorted. In contrast, treating such outcomes as beta-distributed respects these limits and can yield more accurate estimates. Despite these advantages, the use of beta models in applied research remains limited. Our goal is to provide researchers with practical guidance for adopting beta regression models, illustrated with an example drawn from the psychological literature. We begin by introducing the beta distribution and beta regression, emphasizing key components and assumptions. Next, using data from a learning and memory study, we demonstrate how to fit a beta regression model in R with the Bayesian package {brms} and how to interpret results on the response scale. We also discuss model extensions, including zero-inflated, zero- and one-inflated, and ordered beta models. Basic familiarity with regression modeling and R is assumed. To promote wider adoption of these methods, we provide detailed code and materials at <https://zenodo.org/records/16895241>.

*Keywords:* beta regression, beta distribution, R tutorial, psychology, learning and memory

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The analyses herein were not preregistered. Data, code, and materials for this manuscript can be found at <https://zenodo.org/records/16895241>. The authors have no conflicts of interest to disclose. Author roles were classified using the Contributor Role Taxonomy (CRediT; <https://credit.niso.org/>) as follows: Jason Geller: Conceptualization, Data curation, Formal analysis, Project administration, Resources, Visualization, Writing - original draft; Robert Kubinec: Formal analysis, Validation, Writing - review & editing; Chelsea M. Parlett Pelleriti: Formal analysis, Writing - review & editing; Matti Vuorre: Formal analysis, Writing - review & editing

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 Preprint

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## Introduction

3 Many outcomes in psychological research are naturally expressed as proportions or percentages.  
4 These include the proportion of correct responses on a test (e.g., Kornell and Bjork (2008)), the proportion  
5 of time a participant fixates on a stimulus in an eye-tracking task (e.g., James et al., 2025), or the proportion of  
6 respondents endorsing a particular belief (e.g., Costello et al., 2024). A central question for studies involving  
7 proportional data is how to analyze these outcomes in a statistically appropriate and interpretable way.

8 Researchers frequently default to linear models that assume Gaussian (normal) distributions, such  
9 as t-tests, ANOVAs, and linear regression. However, these models make strong assumptions: (1) residuals  
10 are normally distributed, (2) the outcome is unbounded (from  $-\infty$  to  $\infty$ ), and (3) variance is constant across  
11 the range of the data. These assumptions are rarely satisfied in practice (Sladekova & Field, 2024), and they  
12 are especially ill-suited for proportional outcomes, which are bounded between 0 and 1 and often exhibit  
13 heteroscedasticity—non-constant variance, particularly near the boundaries (Ferrari & Cribari-Neto, 2004;  
14 Paolino, 2001; Smithson & Verkuilen, 2006). Violating these assumptions can lead to biased estimates and  
15 spurious inferences, especially when many observations cluster near 0 or 1.

16 In some cases, a generalized linear model (GLM) can relax the assumption of normality. For exam-  
17 ple, binomial and Bernoulli models—often referred to as logistic regression when used with a logit link—are  
18 appropriate when the outcome is binary (0/1) or represents the number of successes out of a fixed number  
19 of trials. These models, however, rely on data that arise from discrete trial structures. They tend to perform  
20 poorly when the observed proportions are truly continuous or when the data show extra variability (overdis-  
21 pension), particularly when many values occur near the boundaries of the scale (0 and 1).

22 The challenges of analyzing proportional data are not new (see Bartlett, 1936). Fortunately, several  
23 existing approaches address the limitations of commonly used models. One such approach is beta regression,  
24 an extension of the generalized linear model that employs the beta distribution (Ferrari & Cribari-Neto, 2004;  
25 Paolino, 2001). Beta regression offers a flexible and robust solution for modeling proportional data directly by  
26 accounting for boundary effects and over-dispersion, making it a valuable alternative to traditional binomial  
27 models. This approach is particularly well-suited for psychological research because it can handle both  
28 the bounded nature of proportional data and the non-constant variance often encountered in these datasets  
29 (Sladekova & Field, 2024). In addition, the direct modeling of proportions allows comparability across tasks  
30 and scales, and can be particularly valuable when only the proportional data is available, as is often the case  
31 with secondary data that lack item-level structure or point values. While usage of these models has faced  
32 obstacles due to theoretical and computational limitations, as we argue in this paper, beta regression and its  
33 extensions now provide an accessible and more robust method to traditional linear modeling.

34 While in this paper we will focus on proportional-responses that lie between 0 and 1—it is important  
35 to note that our analysis applies to any bounded continuous scale. Any bounded scale can be mapped to lie  
36 within 0 and 1 without resulting in a loss of information as the transformation is linear.<sup>1</sup> Consequently, a  
37 scale that has natural end points of -1,234 and +8,451—or any other end points on the real number line short  
38 of infinity—can be modeled using the approaches we describe in this paper.

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<sup>1</sup>Specifically, for any continuous bounded variable  $x$ , we can rescale this variable to lie within 0 and 1 by using the formula  $x' = \frac{x - \min(x)}{\max(x) - \min(x)}$  where  $0 \leq x' \leq 1$ .

**39 A Beta Way Is Possible**

40 With the widespread availability of open-source software such as R (R Core Team, 2024) and its  
41 extensive ecosystem of user-developed packages, advanced models like beta regression have become increasingly  
42 accessible to applied researchers. Yet, their adoption in psychology remains relatively limited. One  
43 contributing factor may be the lack of domain-specific examples that demonstrate how these models address  
44 common challenges in psychological data. Although recent years have seen a growing interest in beta regression,  
45 and a number of useful tutorials are available (Bendixen & Purzycki, 2023; Coretta & Bürkner, 2025;  
46 Heiss, 2021; e.g., Smithson & Verkuilen, 2006; Vuorre, 2019), these resources often either focus on basic  
47 implementation or briefly mention extensions without detailing how they can be applied to psychologically  
48 relevant research questions.

49 The present tutorial aims to help bridge this gap by providing a comprehensive, applied introduction  
50 to beta regression and several of its extensions. In addition to the standard beta model, we walk through zero-  
51 inflated, zero-one-inflated, and ordered beta regression. These models are particularly useful for researchers  
52 working with proportion outcomes that include boundary values (e.g., exact 0s or 1s) or responses with an  
53 inherent ordinal structure. Our goal is to offer practical guidance that enables psychological researchers to  
54 implement, interpret, and report these models in ways that directly support their empirical questions.

55 Beyond model specification, we place strong emphasis on interpreting results on the response scale—  
56 that is, in terms of probabilities and proportions—rather than relying on often difficult to interpret parameters.  
57 This focus makes the models more accessible and meaningful for psychological applications, where effects  
58 are often easier to communicate when framed on the original scale of the outcome (e.g., changes in recall  
59 accuracy or task performance). Throughout, we provide reproducible code and annotated examples to help  
60 readers implement and interpret these models in their own work.

61 We begin the tutorial with a non-technical overview of the beta distribution and its core  
62 parameters. We then walk through the process of estimating beta regression models using the R package  
63 `{brms}` (Bürkner, 2017), illustrating each step with applied examples. To guide interpretation, we emphasize  
64 coefficients, predicted probabilities, and marginal effects calculated using the `{marginaleffects}`  
65 package (Arel-Bundock et al., 2024). We also introduce several useful extensions—zero-inflated (ZIB),  
66 zero-one-inflated (ZOIB), and ordered beta regression—that enable researchers to model outcomes that in-  
67 clude boundary values. Finally, all code and materials used in this tutorial are fully reproducible and  
68 available via our GitHub repository: [https://github.com/jgeller112/beta\\_regression\\_tutorial](https://github.com/jgeller112/beta_regression_tutorial) and on Zenodo  
69 <https://zenodo.org/records/16895241><sup>2</sup>.

**70 Beta Distribution**

71 Proportional data pose some challenges for standard modeling approaches: The data are bounded  
72 between 0 and 1 and often exhibit non-constant variance (heteroscedasticity) (Ferrari & Cribari-Neto, 2004;  
73 Paolino, 2001). Common distributions used within the generalized linear model frameworks often fail to  
74 capture these properties adequately, which can necessitate alternative modeling strategies.

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<sup>2</sup>In this article, we try to limit code where possible; however, the online version has all the code needed to reproduce all analyses herein. Furthermore, to promote transparency and reproducibility, the tutorial was written in R version 4.5.1 (R Core Team (2024)) using Quarto (v.1.5.54), an open-source publishing system that allows for dynamic and static documents. This allows figures, tables, and text to be programmatically included directly in the manuscript, ensuring that all results are seamlessly integrated into the document. In addition, we use the `rix` (Rodrigues & Baumann, 2025) R package which harnesses the power of the `nix` (Dolstra & contributors, 2006) ecosystem to help with computational reproducibility. Not only does this give us a snapshot of the packages used to create the current manuscript, but it also takes a snapshot of system dependencies used at run-time. This way reproducers can easily re-use the exact same environment by installing the `nix` package manager and using the included `default.nix` file to set up the right environment. The README file in the GitHub repository contains detailed information on how to set this up to reproduce the contents of the current manuscript, including a video.

75 While we do not have time to delve fully into its derivation, the beta distribution is useful for modeling bounded continuous scales because it is the distribution for the probability of an event. Given that a  
 76 probability can take on any value from near 0 (the event will not occur with certainty) to 1 (the event will  
 77 occur with certainty), the beta distribution can likewise take on virtually any value in that bounded interval.  
 78 As a consequence, the beta distribution is the maximum entropy distribution for *any* bounded continuous  
 79 random variable, which means that the beta distribution can represent the full range of possibilities of such a  
 80 scale.<sup>3</sup> As a consequence, if we have a continuous scale with upper and lower bounds—and no other special  
 81 conditions—the beta distribution will in principle provide a very good approximation of the uncertainty of the  
 82 scale.

83 Typically, the expected value (or mean) of the response variable is the central estimand scholars want  
 84 to estimate. A model should specify how this expected value depends on explanatory variables through two  
 85 main components: a linear predictor, which combines the explanatory variables in a linear form ( $a + b_1x_1 +$   
 86  $b_2x_2$ , etc.), and a link function, which connects the expected value of the response variable to the linear  
 87 predictor (e.g.,  $E[Y] = g(a + b_1x_1 + b_2x_2)$ ). In addition, a random component specifies the distribution  
 88 of the response variable around its expected value (such as Poisson or binomial distributions, which belong  
 89 to the exponential family) (Nelder & Wedderburn, 1972). Together, these components provide a flexible  
 90 framework for modeling data with different distributional properties.

91 The beta distribution is continuous and restricted to values between 0 and 1 (exclusive). Its two  
 92 parameters—commonly called shape1 ( $\alpha$ ) and shape2 ( $\beta$ )—govern the distribution’s location, skewness, and  
 93 spread. By adjusting these parameters, the distribution can take many functional forms (e.g., it can be sym-  
 94 metric, skewed, U-shaped, or even approximately uniform; see Figure 1).

95 To illustrate, consider a test question worth seven points. Suppose a participant scores five out of  
 96 seven. The number of points received (5) can be treated as  $\alpha$ , and the number of points missed (2) as  $\beta$ . The  
 97 resulting beta distribution would be skewed toward higher values, reflecting a high performance (yellow line  
 98 in Figure 1; “beta(5, 2)”). Reversing these values would produce a distribution skewed toward lower values,  
 99 representing poorer performance (green line in Figure 1; “beta(2, 5)”).

## 101 I Can’t Believe It’s Not beta

102 While the standard parameterization of the beta distribution uses  $\alpha$  and  $\beta$ , a reparameterization to a  
 103 mean ( $\mu$ ) and precision ( $\phi$ ) is more useful for regression models. The mean represents the expected value  
 104 of the distribution, while the dispersion, which is inversely related to variance, reflects how concentrated  
 105 the distribution is around the mean, with higher values indicating a narrower distribution and lower values  
 106 indicating a wider one. The connections between the beta distribution’s parameters are shown in Equation 1.  
 107 Importantly, the variance depends on the average value of the response because uncertainty intervals need to  
 108 adjust for how close the value of the response is to the boundary.

Shape 1: $a = \mu\phi$	Mean: $\mu = \frac{a}{a + b}$	(1)
Shape 2: $b = (1 - \mu)\phi$	Precision: $\phi = a + b$	
	Variance: $var = \frac{\mu \cdot (1 - \mu)}{1 + \phi}$	

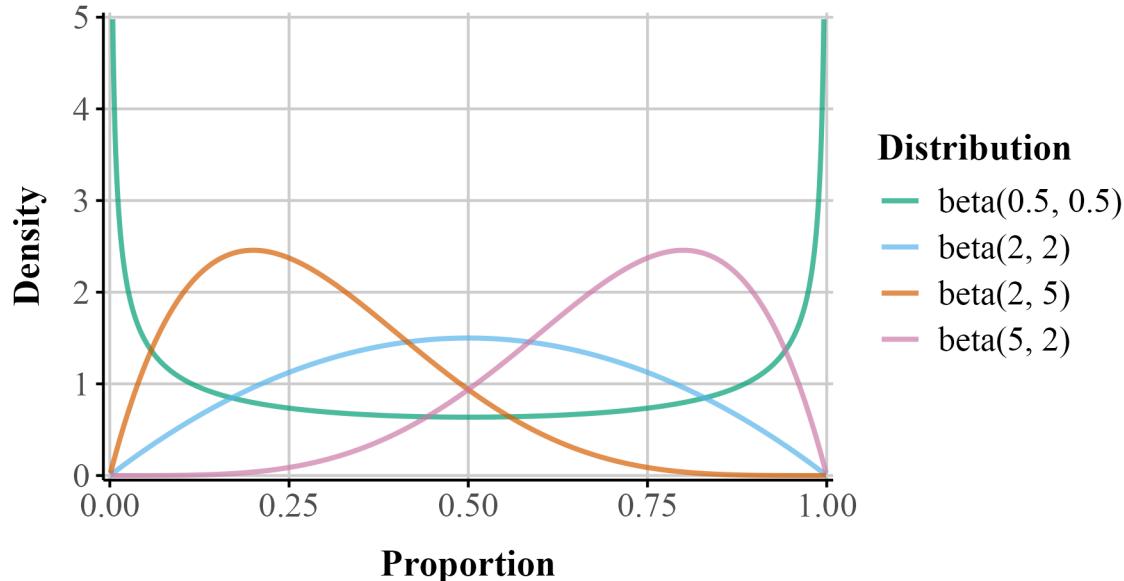
109 Thus, beta regression allows modeling both the mean and precision of the outcome distribution. To  
 110 ensure that  $\mu$  stays between 0 and 1, we apply a link function, which allows linear modeling of the mean on  
 111 an unbounded scale. A common link-function choice is the logit, but other functions such as the probit or  
 112 complementary log-log are possible.

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<sup>3</sup>Technically, this maximum entropy condition is satisfied because the beta(1,1) distribution is uniform over its support. In addition, we assume that the scale has been re-scaled to the [0, 1] interval as we describe above.

**Figure 1**

*beta distributions with different shape1 and shape2 parameters.*



113        The logit function,  $\text{logit}(\mu) = \log\left(\frac{\mu}{1-\mu}\right)$  links the mean to log-odds which are unbounded, making  
 114      linear modeling possible. The logit here no longer carries the same literal *odds* interpretation because there  
 115      are no corresponding counts of “successes” and “failures.” Instead, the logit transform here simply maps the  
 116      mean of the distribution to the real line. The inverse of the logit, called the logistic function, maps the linear  
 117      predictor  $\eta$  back to the original scale of the data  $\left(\mu = \frac{1}{1+e^{-\eta}}\right)$ . The coefficients describe how predictors shift  
 118      the *average proportion* on the logit scale here. Similarly, the strictly positive dispersion parameter is usually  
 119      modeled through a log link function, ensuring it remains positive.

120        By accounting for the observations’ natural limits and non-constant variance across different val-  
 121      ues, the beta distribution is useful in psychology where outcomes like performance rates or response scales  
 122      frequently exhibit these features.

### 123      Bayesian Approach to Beta Regression

124        Beta regression models can be estimated using either frequentist or Bayesian methods. In this paper,  
 125      we adopt a Bayesian framework because it facilitates the estimation and interpretation of more complex  
 126      models (Gelman et al., 2013; Johnson et al., 2022; McElreath, 2020). Additionally, the use of Bayesin  
 127      statistics in psychology has been steadily growing (Pfadt et al., 2025). In principle, frequentist methods  
 128      like maximum likelihood can be framed as Bayesian models with uninformative priors, and as a result, the  
 129      modeling perspective we put forward in this paper can apply to either approach. Nonetheless, we note that  
 130      in highly non-linear and hierarchical models, frequentist estimation may require additional adjustments such  
 131      as bootstrapping to obtain proper uncertainty intervals, whereas Bayesian modeling handles these extensions  
 132      more naturally via exploration of the full joint posterior distribution.<sup>4</sup>

<sup>4</sup>A common concern is that Bayesian methods are slower than frequentist ones. While this is true in general, modern Bayesian computation engines are efficient, and in explanatory modeling our priority is to specify appropriate estimands rather than to optimize for computation speed. Moreover, we use the {brms} package (Bürkner, 2017), which provides a high-level interface to Stan (Team, 2023) and uses familiar R formula syntax (similar to `lm()`), making advanced Bayesian modeling accessible to researchers with standard regression backgrounds. The package also supports parallelization, which substantially reduces computation time for large

133 There are several important differences between our Bayesian analysis and the frequentist methods  
 134 readers may be more familiar with—most notably, the absence of  $t$ - and  $p$ -values. To estimate models, the  
 135 `{brms}` package uses Stan’s computational algorithms to draw random samples from the posterior distribu-  
 136 tion, which represents uncertainty about the model parameters. This posterior is conceptually analogous to  
 137 a frequentist sampling distribution. By default, Bayesian models run 4 chains with 2,000 iterations each.<sup>5</sup>  
 138 The first 1,000 iterations per chain are warmup and are discarded. The remaining 1,000 iterations per chain  
 139 are retained as posterior draws, yielding 4,000 total post-warmup draws across all chains. From these draws,  
 140 we can compute the posterior mean (analogous to a frequentist point estimate) and the 95% credible interval  
 141 (Cr.I.), which is often compared to a confidence interval.

142 In addition, an important part of Bayesian analyses is prior specification. Priors encode our assump-  
 143 tions about plausible parameter values before observing the data and allow the model to regularize estimates,  
 144 especially when data are sparse or parameters are weakly identified. To help bridge the conceptual gap for  
 145 users more familiar with frequentist models, we begin with the default priors (flat/non-informative) provided  
 146 by `{brms}`. These priors are intentionally non-informative, and in many applications produce results that  
 147 closely align with frequentist estimates, while still offering the flexibility and interpretive advantages of a  
 148 Bayesian framework. We strongly urge readers to consider prior specification strongly in all their work.

149 To ease readers into Bayesian data analysis we provide a metric known as the *probability of direc-  
 150 tion* (*pd*), which reflects the probability that a parameter is strictly positive or negative. When a uniform  
 151 prior is used (all values equally likely in the prior), a *pd* of 95%, 97.5%, 99.5%, and 99.95% corresponds  
 152 approximately to two-sided *p*-values of .10, .05, .01, and .001 (i.e.,  $\text{pd} \approx 1 - p/2$  for symmetric posteriors  
 153 with weak/flat priors) (see Figure 2 for an illustrative comparison). For directional hypotheses, the *pd* can be  
 154 interpreted as roughly equivalent to one minus the *p*-value (Marsman & Wagenmakers, 2016).

155 For reasons of space, we refer readers unfamiliar to Bayesian data analysis to several existing books  
 156 on the topic (Gelman et al., 2013; Kruschke, 2015; McElreath, 2020). In addition, we assume readers are  
 157 familiar with R, but those in need of a refresher should find Wickham et al. (2023) useful.

## 158 Beta Regression Tutorial

### 159 Example Data

160 Throughout this tutorial, we analyze data from a memory experiment examining whether the flu-  
 161 ency of an instructor’s delivery affects recall performance (Wilford et al., 2020, Experiment 1A). Instructor  
 162 fluency—marked by expressive gestures, dynamic vocal tone, and confident pacing—has been shown to  
 163 influence students’ perceptions of learning, often leading learners to rate fluent instructors more favorably  
 164 (Carpenter et al., 2013). However, previous research suggests that these impressions do not reliably translate  
 165 into improved memory performance (e.g., Carpenter et al., 2013; Toftness et al., 2017; Witherby &  
 166 Carpenter, 2022). In contrast, Wilford et al. (2020) found that participants actually recalled more information  
 167 after watching a fluent instructor compared to a disfluent one. This surprising finding makes the dataset a  
 168 compelling case study for analyzing proportion data, as recall was scored out of 10 possible idea units per  
 169 video.

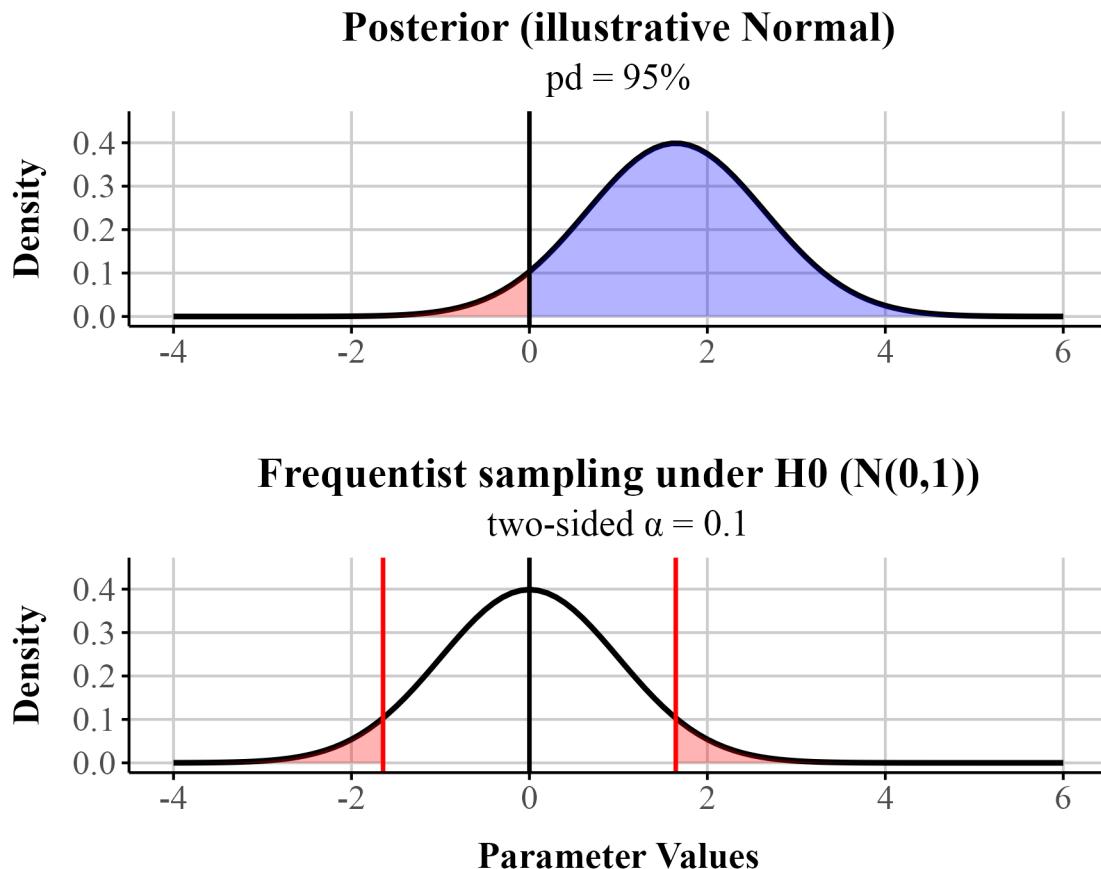
170 In Experiment 1A, participants ( $N = 96$ ) watched two short instructional videos, each delivered  
 171 either fluently or disfluently. Fluent videos featured instructors with smooth delivery and natural pacing,  
 172 while disfluent videos included hesitations, monotone speech, and awkward pauses. After a distractor task,  
 173 participants completed a free recall test, writing down as much content as they could remember from each  
 174 video within a three-minute window. Their recall was then scored for the number of idea units correctly  
 175 remembered.

datasets.

<sup>5</sup>The Hamiltonian Monte Carlo sampler employed by Stan, which we also use in this paper, can converge with significantly fewer iterations, though rapid convergence depends on model complexity, which is why we use a more conservative standard in this paper.

**Figure 2**

A Bayesian posterior distribution (assuming a uniform prior) centered at a point estimate chosen so that the probability of direction ( $pd$ ) equals 0.95, and a frequentist sampling distribution (under the null; centered at 0). In the Bayesian posterior distribution, the blue area represents the  $pd$ , and the red area represents the remaining  $1 - pd$  of the distribution. In the frequentist sampling distribution, the red tail areas represent the rejection region at  $\alpha = 0.10$ . In this example, the posterior mean lies exactly at the  $1 - \frac{\alpha}{2}$  quantile of the null sampling distribution. For symmetric posteriors with flat priors, the  $pd$  is numerically equivalent to the one-sided  $p$ -value.



---

**Listing 1** Data needed to run examples

---

```
# get data here from project folder
fluency_data -> read_csv(here::here("data", "fluency_data.csv"))
```

---

**Table 1**

*Four observations from Wilford et al. (2020). Accuracy refers to the proportion of correctly recalled idea units.*

Participant	Fluency	Accuracy
64	Disfluent	0.10
30	Fluent	0.60
12	Fluent	0.10
37	Fluent	0.35

Our primary outcome variable is the proportion of idea units recalled on the final test, calculated by dividing the number of correct units by 10. We show a sample of these data in Table 1. The dataset can be downloaded from GitHub (Listing 1). Because this is a bounded continuous variable (i.e., it ranges from 0 to 1), it violates the assumptions of typical linear regression models that treat outcomes as normally distributed. Despite this, it remains common in psychological research to analyze proportion data using models that assume normality. In what follows, we reproduce Wilford et al. (2020)'s analysis and then re-analyze the data using beta regression and highlight how it can improve our inferences.

**Reanalysis of Wilford et al. Experiment 1A**

In their original analysis of Experiment 1A, Wilford et al. (2020) compared memory performance between fluent and disfluent instructor conditions using a traditional independent-samples t-test on mean accuracy for 96 participants. They found that participants who watched the fluent instructor recalled significantly more idea units than those who viewed the disfluent version (see Figure 3).

We first replicate this analysis in a regression framework using {brms}. We model final test mean accuracy—the proportion of correctly recalled idea units across the videos—as the dependent variable. Our predictor is instructor fluency, with two levels: Fluent and Disfluent. We use treatment (dummy) coding, which is the default in R. This coding scheme sets the first level of a factor (in alphabetical order) as the reference level. In this case, Disfluent is the reference, and the coefficient for Fluent reflects the contrast between fluent and disfluent instructor conditions.

**Regression Model**

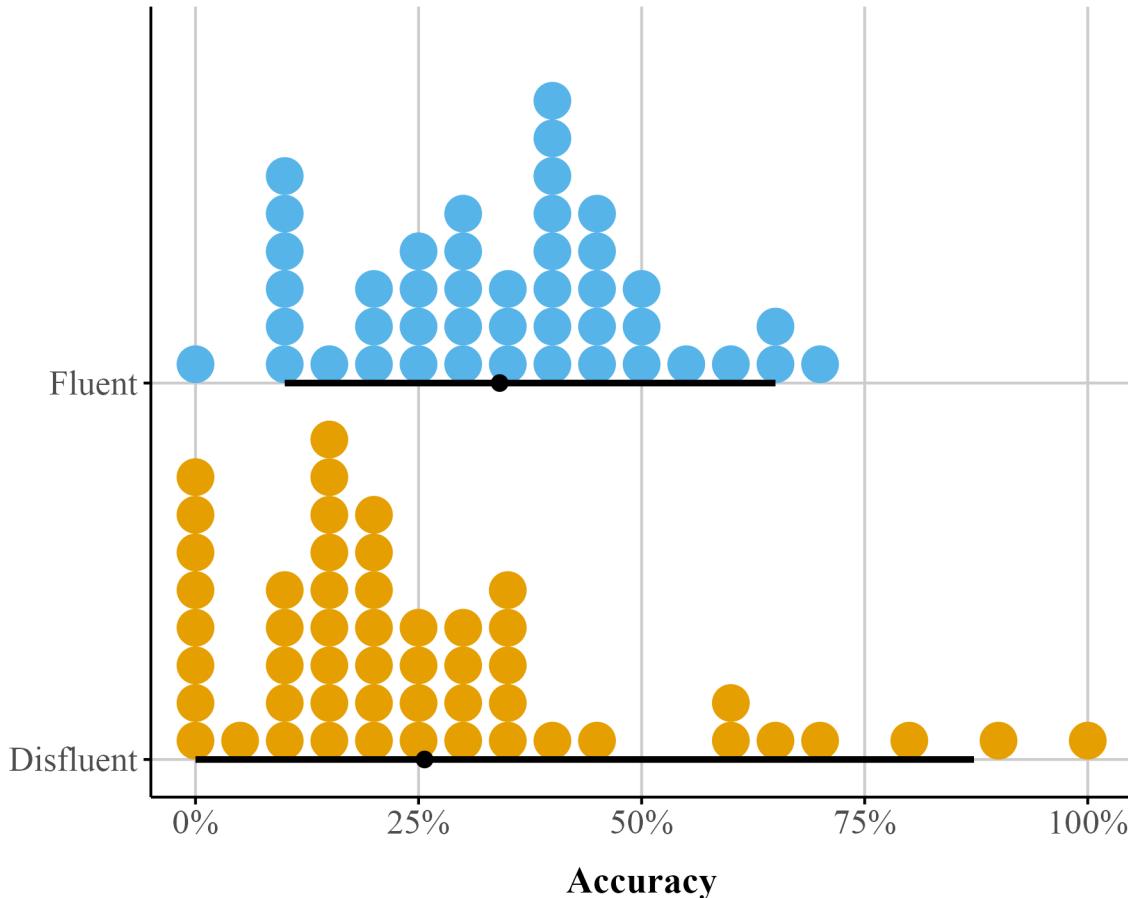
We first start by loading the brms (Bürkner, 2017) and cmdstanr (Gabry et al., 2024) packages (Listing 2). We use the cmdstanr backend for Stan (Team, 2023) because it's faster than the default used to run models (i.e., rstan),<sup>6</sup> though all of these models can also be fit with brms defaults.

We fit the model using the brm() function from the brms package (Listing 3). Although not shown here, we ran the models using four chains (the default), executed in parallel across four cores. When the model is run in Listing 3, the model summary output will appear in the R console. The output from

<sup>6</sup>In order to use the cmdstanr backend you will need to first install the package (see <https://mc-stan.org/cmdstanr/>) and also run cmdstanr::install\_cmdstan() if you have not done so already.

**Figure 3**

*Dot plot depicting accuracy distributions for the Fluent and Disfluent conditions. Each condition shows individual data points and summary statistics (mean and 95% percentile interval) to illustrate variability and central tendency.*

**Listing 2** Load the `brms` and `cmdstanr` packages

---

```
library(brms)
library(cmdstanr)
```

---

201 bayes\_reg\_model shows each parameter's posterior summary: The posterior distribution's mean and stan-  
 202 dard deviation (analogous to the frequentist standard error) and its 95% credible interval, which indicate the  
 203 95% of the most credible parameter values. In brms, the reported Cr.I is an equal-tailed interval, meaning  
 204 that the probability mass excluded from the interval is split equally between the lower and upper tails. Ad-  
 205 ditionally, the output indicates numerical estimates of the sampling algorithm's performance: Rhat should  
 206 be close to one, and the ESS (effective sample size) metrics should be as large as possible given the number  
 207 of iterations specified (default is 4000). Generally, ESS  $\geq 1000$  is recommended (Bürkner, 2017). For the  
 208 models we present in this paper, convergence is trivial with standard linear models, though we note that these  
 209 metrics are still important to pay attention to in case of model misfit.

210 Our main question of interest is: what is the causal effect of instructor fluency on final test perfor-

---

**Listing 3** Fitting a gaussian model with brm().

---

```

bayes_reg_model <- brm(
  Accuracy ~ Fluency,
  data = fluency_data,
  family = gaussian(),
  file = here::here("manuscript", "models", "model_reg_bayes")
)

```

---

211 mance? In order to answer this question, we will have to look at the output summary produced by Listing 3  
 212 (also see Table 8 under Bayesian LM). the Intercept refers to the posterior mean accuracy in the disfluent  
 213 condition,  $M = 0.257$ , as fluency was dummy-coded. The fluency coefficient (FluencyFluent) reflects the  
 214 mean posterior difference in recall accuracy between the fluent and disfluent conditions:  $b = 0.084$ . The 95%  
 215 Cr.I for this estimate spans from 0 to 0.168. These values are shown in the “95% Cr.I” columns of the output.  
 216 These results closely mirror the findings reported by Wilford et al. (2020) (Experiment 1A).

```

217 Family: gaussian
218 Links: mu = identity; sigma = identity
219 Formula: Accuracy ~ Fluency
220 Data: fluency_data (Number of observations: 96)
221
222 Regression Coefficients:
223             Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
224 Intercept      0.26      0.03    0.20    0.32 1.00     4127    2773
225 FluencyFluent  0.08      0.04    0.00    0.17 1.00     4016    3083
226
227 Further Distributional Parameters:
228             Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
229 sigma        0.21      0.02    0.18    0.24 1.00     3869    3024

```

230 The output also includes the effective sample size (ESS) and R (R-hat) values, both of which fall  
 231 within acceptable ranges, indicating good model convergence. Throughout the tutorial, we focus primarily  
 232 on posterior mean estimates and their 95% credible intervals. In addition, we report the pd measure in the  
 233 main summary table (Table 8), provided by the {bayestestR} package (Makowski, Ben-Shachar, Chen, et  
 234 al., 2019; Makowski, Ben-Shachar, & Lüdecke, 2019). This measure offers an intuitive parallel to  $p$ -values,  
 235 which many readers may find familiar. For example, the fluency effect has a pd of .977, indicating a high  
 236 probability that the effect is positive rather than negative (akin to  $p < .05$ ).

237 Importantly, pd does not indicate whether an effect is meaningfully different from a point value—it  
 238 only reflects the proportion of the posterior in one direction. To address questions of practical significance,  
 239 we encourage readers to consider the Region of Practical Equivalence (ROPE) with the Cr.Is (Kruschke,  
 240 2015). Unlike a hypothesis test of a point null (e.g., exactly zero), the ROPE defines a range of values that  
 241 are deemed too small to be of substantive importance. As a rule of thumb (see Kruschke, 2018), if more than  
 242 95% of the posterior distribution lies inside the ROPE, the effect can be considered practically equivalent  
 243 to that negligible range. If less than 5% lies inside, the effect can be considered meaningfully different.  
 244 Intermediate cases are typically labeled undecided.

245 The rope() function in the {bayestestR} package computes the proportion of the posterior within  
 246 the ROPE to facilitate this evaluation. By default, from bayesian models fit via brms the package determines

<sup>247</sup> a ROPE based on the data (roughly reflecting “negligible” effects), but these defaults should be used cau-  
<sup>248</sup> tiously. The choice of ROPE should ultimately be guided by theoretical considerations, prior research, and  
<sup>249</sup> the substantive context of the study. In Listing 4, we show how to compute this using bayestestR. Running  
<sup>250</sup> the function with default settings suggests that less than 5% of the posterior distribution lies within the default  
<sup>251</sup> ROPE (indicating the effect is larger than .02) (see Figure 4). Going forward we do not include a discussion  
<sup>252</sup> of ROPE values, but we encourage readers to adopt it in their own research when appropriate.

---

**Listing 4** Getting ROPE from `bayes_reg_model` object using `rope` function from {bayestestR}

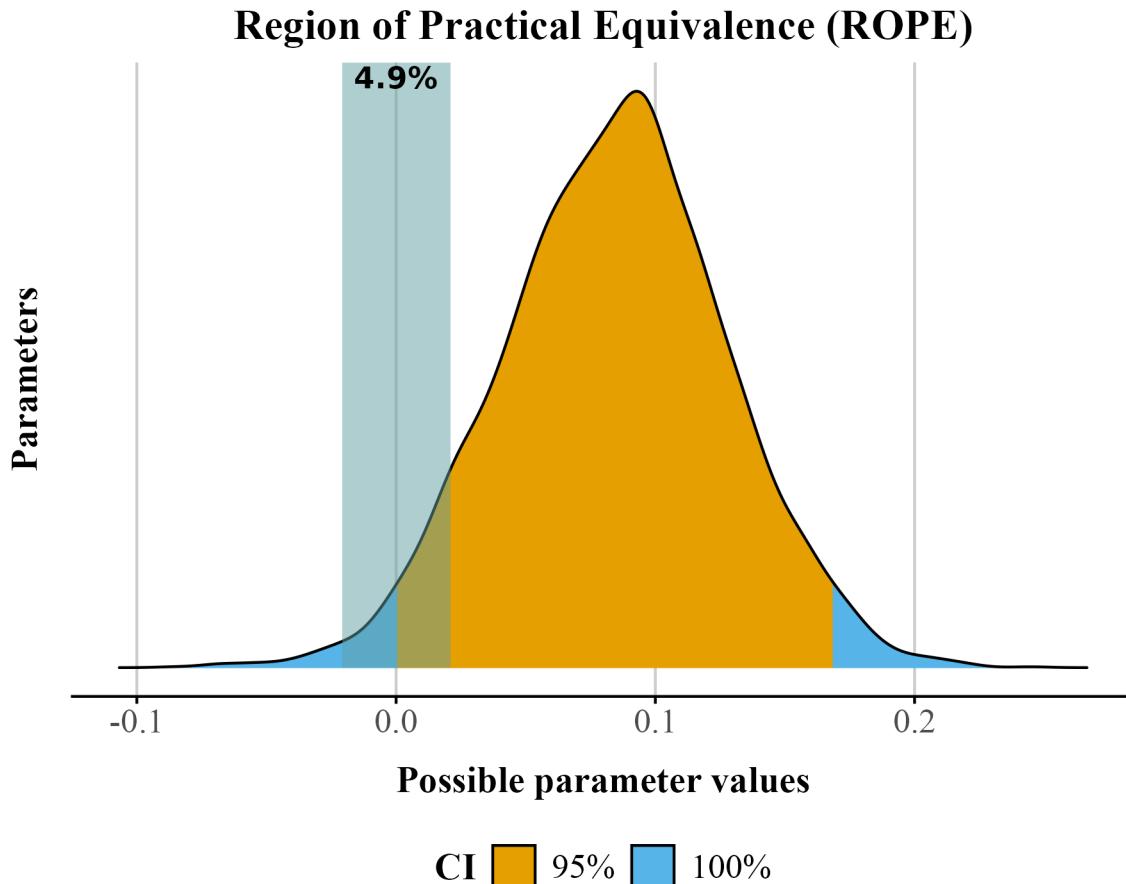
---

```
brms_rope <- bayestestR::rope(bayes_reg_model, ci = .95, ci_method = "ETI")
```

---

**Figure 4**

*Posterior distribution for the fluency effect showing the ROPE(shaded area) with 95% credible interval (orange) and 100% credible interval (blue). The percentage indicates the proportion of the posterior within the ROPE.*



<sup>253</sup> Wilford et al. (2020) observed that instructor fluency impacts actual learning, using a standard  $t$ -test  
<sup>254</sup> on the mean accuracy. But recall this approach assumes normality of residuals and homoscedacity. These  
<sup>255</sup> assumptions are unrealistic when the response values approach the scale boundaries (Sladekova & Field,  
<sup>256</sup> 2024). Does the data we have meet those assumptions? We can use the function `check_model()` from

257 `{easystats}` (Lüdecke et al., 2022) to check our assumptions easily. The code in Listing 5 automatically  
 258 produces Figure 5. We can see some issues with our data. Specifically, there appears to be violations of  
 259 constant variance across the values of the scale (homoskedasticity). In plain terms, this type of model mis-  
 260 specification means that a standard OLS model can predict non-sensical values outside the bounds of the  
 261 scale.

---

**Listing 5** Checking assumptions with the `check_model()` from `easystats` package .

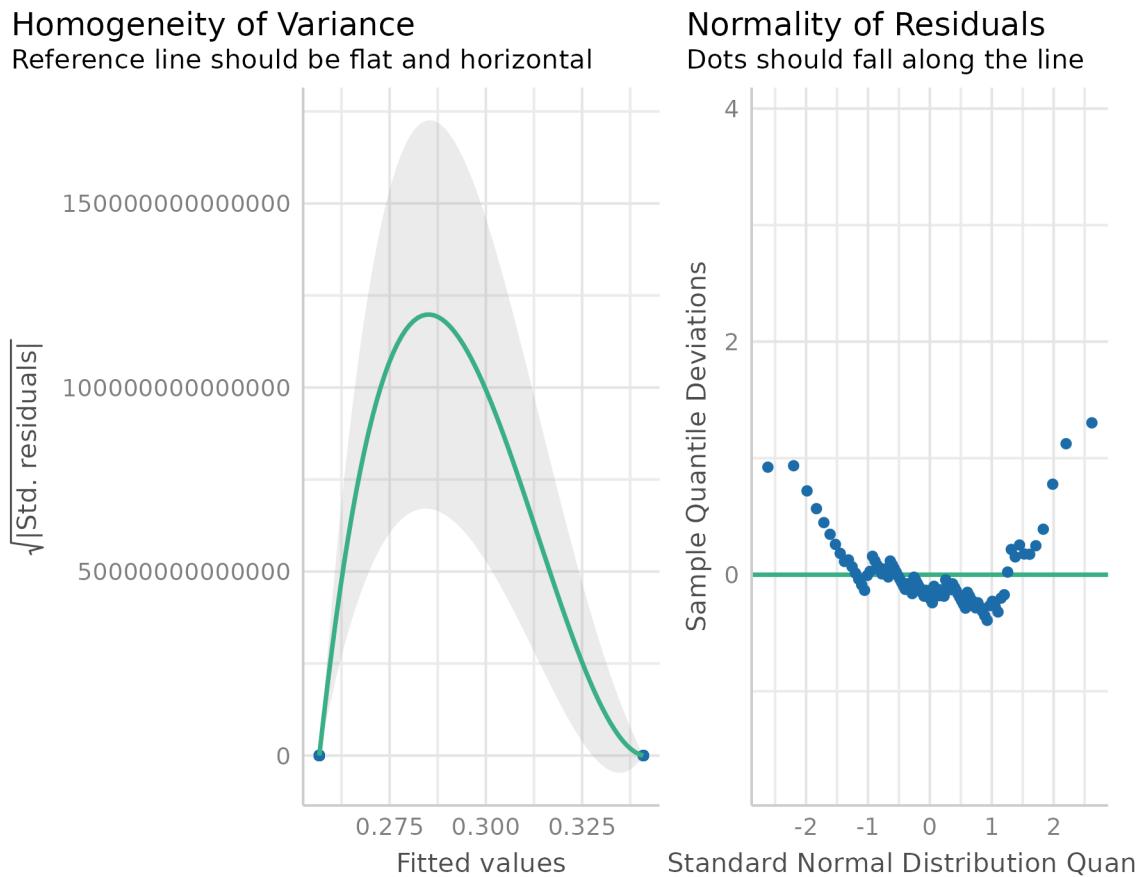
---

```
check_model(bayes_reg_model, check = c("homogeneity", "qq"))
```

---

**Figure 5**

*Two assumption checks for our OLS model: Normality (right) and Homoskedasticity (left)*



262 We can also examine how well the data fits the model by performing a posterior predictive check  
 263 using the `pp_check()` function from `{brms}`. A posterior predictive check involves looking at multiple  
 264 draws or repetitions from the posterior distribution and plotting it against the observed data. Ideally, the  
 265 predictive draws (the light blue lines) should show reasonable resemblance with the observed data (dark blue  
 266 line). In our example (see Figure 12 (A)) the model-predicted density is slightly too peaked and narrow  
 267 compared to the data. In addition, some of the draws extend into negative accuracy values.

268 **Distributional Regression - Beta Regression**

269 It is important to note that there are several justifiable approaches for addressing the distributional  
 270 issues observed in the data. For instance, one could analyze median accuracy instead of the mean, use some  
 271 type of robust estimator for heterogeneity, or apply non-parametric methods to relax some of the model as-  
 272 sumptions. However, in a Bayesian framework, we can address these issues more directly and transparently  
 273 by fitting distributional models (Kneib et al., 2023; Kruschke, 2013). A key advantage of Bayesian distribu-  
 274 tional modeling approach is that we are not limited to modeling only the mean or median of the outcome;  
 275 we can also model parameters such as the variance (or other shape parameters) as functions of predictors.  
 276 This allows us to examine how instructor fluency may influence not only average performance, but also the  
 277 variability in performance across students. If we wanted to keep our mean accuracy variable and continue to  
 278 use a Gaussian model, we could use a distributional approach and model the effect of fluency on  $\sigma$ .

279 Given the outcome variable is proportional, another solution would be to run a beta regression model.  
 280 Again, we can create the beta regression model in brms. In brms, we model each parameter independently.  
 281 Recall from the introduction that in a beta model we model two parameters— $\mu$  and  $\phi$ . Again we do this by  
 282 using the bf() function from brms (Listing 6). We fit two formulas, one for  $\mu$  and one for  $\phi$  and store it  
 283 in the model\_beta\_bayes object below. In the below bf() call, we are modeling Fluency as a function of  
 284 Accuracy only for the  $\mu$  parameter. For the  $\phi$  parameter, we are only modeling the intercept value. This is  
 285 saying dispersion does not change as a function of fluency.

286 To run our beta regression model, we need to exclude 0s and 1s in our data set. If we try to run  
 287 a model with our data data\_fluency we get an error: `Error: Family 'beta' requires response`  
 288 `greater than 0`. This is because the beta distribution only supports observations in the 0 to 1 interval  
 289 `excluding exact 0s and 1s`. We need make sure there are no 0s and 1s in our dataset.

290 The dataset contains nine 0s and one 1. One approach is to nudge our 0s towards .01 and our 1s to  
 291 .99, or apply a special formula (Smithson & Verkuilen, 2006) so values fall within the [0, 1] interval. We  
 292 implore readers not to engage in this practice. Kubinec (2022) showed that this practice can result in serious  
 293 distortion of the outcome as the sample size grows larger, resulting in ever smaller values that are “nudged”.  
 294 Because the beta distribution is a non-linear model of the outcome, values that are very close to the boundary,  
 295 such as 0.00001 or 0.99999, will be highly influential outliers. To run this beta model we will remove the 0s  
 296 and 1s, and later in this article we will show how to jointly model these scale end points with the rest of the  
 297 data. The model from Listing 6 uses a transformed data\_fluency object (called data\_beta) where 0s and  
 298 1s are removed. When we run this code we should not get an error.

299 **Model Parameters.** In Table 8, under the beta regression column, the coefficient with b\_ represents  
 300 how fluency of instructor influences the  $\mu$  parameter estimates (which is the mean of the distribution here).  
 301 These coefficients are interpreted on the scale of the logit, meaning they represent linear changes on a non-  
 302 linear space. The intercept term (b\_Intercept) represents the log odds of the mean on accuracy for the  
 303 fluent instructor. Log odds that are negative indicate that it is more likely a “success” (like getting the correct  
 304 answer) will NOT happen than that it will happen. Similarly, regression coefficients in log odds forms that  
 305 are negative indicate that an increase in that predictor leads to a decrease in the predicted probability of a  
 306 “success”.

307 The other component we need to pay attention to is the dispersion or precision parameter coefficients  
 308 labeled as phi in Table 8. The dispersion ( $\phi$ ) parameter tells us how precise our estimate is. Specifically,  
 309  $\phi$  in beta regression tells us about the variability of the response variable around its mean. Specifically, a  
 310 higher dispersion parameter indicates a narrower distribution, reflecting less variability. Conversely, a lower  
 311 dispersion parameter suggests a wider distribution, reflecting greater variability. The main difference between  
 312 a dispersion parameter and the variance is that the dispersion has a different interpretation depending on the  
 313 value of the outcome, as we show below. The best way to understand dispersion is to examine visual changes  
 314 in the distribution as the dispersion increases or decreases.

---

**Listing 6** Fitting a beta model without 0s and 1s in brm().

---

```
# set up model formal
model_beta_bayes <- bf(
  Accuracy ~ Fluency, # fit mu model
  phi ~ 1 # fit phi model
)

# transform 0 to 0.1 and 1 to .99
data_beta <- fluency_data |>
  filter(
    Accuracy != 0,
    Accuracy != 1
  )

beta_brms <- brm(
  model_beta_bayes,
  data = data_beta,
  family = Beta(),
  file = here::here("manuscript", "models", "model_beta_bayes_reg_01")
)
```

---

315        Understanding the dispersion parameter helps us gauge the precision of our predictions and the  
 316 consistency of the response variable. In `beta_brms` we only modeled the dispersion of the intercept. When  
 317  $\phi$  is not specified, the intercept is modeled by default (see Table 8). It represents the overall dispersion in  
 318 the outcome across all conditions. Instead, we can model different dispersions across levels of the Fluency  
 319 factor. To do so, we add `Fluency` to the `phi` model in `bf()`. We model the precision (`phi`) of the `Fluency`  
 320 factor by using a `~` and adding factors of interest to the right of it (Listing 7).

---

**Listing 7** Fitting beta model with dispersion in brm().

---

```
model_beta_bayes_disp <- bf(
  Accuracy ~ Fluency, # Model of the mean
  phi ~ Fluency # Model of the precision
)

beta_brms_dis <- brm(
  model_beta_bayes_disp,
  data = data_beta,
  family = Beta(),
  file = here::here("manuscript", "models", "model_beta_bayes_dis_run01")
)
```

---

321        Table 8 displays the model summary with the precision parameter labeled as `phi_Fluency`. Since  $\phi$   
 322 is modeled on the log scale, the coefficients represent changes in  $\log-\phi$  rather than  $\phi$  itself. To see the effect  
 323 in the original units, we convert the values back by exponentiating. Thus, the effect of the Fluent condition

324 can be understood by comparing the exponentiated predicted  $\phi$  in the Fluent condition to that in the baseline  
 325 condition.

326 The  $\phi$  parameters are estimated on the log scale. The term  $\beta_{\text{Intercept}}^{(\phi)}$  represents the log-precision for  
 327 the reference (disfluent) condition. The coefficient  $\beta_{\text{FluencyFluent}}^{(\phi)}$  represents the change in log-precision when  
 328 moving from the disfluent to the fluent condition.

329 To obtain precision on the original scale, we exponentiate the linear predictor:

$$\phi_{\text{disfluent}} = \exp(\beta_{\text{Intercept}}^{(\phi)}), \quad \phi_{\text{fluent}} = \exp(\beta_{\text{Intercept}}^{(\phi)} + \beta_{\text{FluencyFluent}}^{(\phi)}).$$

330 The coefficient  $\beta_{\text{FluencyFluent}}^{(\phi)}$  therefore describes a *multiplicative* change in precision. Specifically,

$$\frac{\phi_{\text{fluent}}}{\phi_{\text{disfluent}}} = \exp(\beta_{\text{FluencyFluent}}^{(\phi)}).$$

331 Because the 95% credible interval for  $\beta_{\text{FluencyFluent}}^{(\phi)}$  does not include zero, we infer that there is a  
 332 credible difference in precision between the fluent and disfluent conditions.

333 It is important to note that these estimates are not the same as the marginal effects we discussed  
 334 earlier. Changes in dispersion affect the spread or variability of the response distribution without necessarily  
 335 altering its mean. This makes dispersion particularly relevant for research questions that focus on features  
 336 of the distribution beyond the average—such as how concentrated responses are. For instance, high disper-  
 337 sion might indicate that individuals cluster at the extremes (e.g., very high or very low ratings), suggesting  
 338 clustering in the outcome.

339 A critical assumption of the linear model is homoscedasticity, which means constant variance of the  
 340 errors. WIth beta regression model we can include a dispersion parameter for Fluency. Properly accounting  
 341 for dispersion is crucial because it impacts the precision of our mean estimates and, consequently, the sig-  
 342 nificance of our coefficients. The inclusion of dispersion in the our model increased the uncertainty of the  $\mu$   
 343 coefficient (see Figure 6). This suggests that failing to account for the dispersion of the variables might lead  
 344 to biased estimates. This highlights the potential utility of an approach like beta regression over a traditional  
 345 approach as beta regression can explicitly model dispersion and address issues of heteroscedasticity.

346 While it is advisable to model precision, if there is uncertainty about the best model, a relatively  
 347 agnostic approach would be to compare models, for example with leave one out (loo) cross validation, to  
 348 examine if a dispersion parameter should be considered in our model.<sup>7</sup>

### 349 **Predicted Probabilities**

350 Parameter estimates are usually difficult to interpret on their own and can require a lot of mathe-  
 351 matical gymnastics to get the estimate you need. We argue that researchers should not spend too much time  
 352 interpreting raw coefficients from non-linear models. We report them in this tutorial for completeness. In-  
 353 stead researchers should discuss the effects of the predictor on the actual outcome of interest (in this case the  
 354 0-1 scale). The logit link allows us to transform back and forth between the scale of a linear model and the  
 355 nonlinear scale of the outcome, which is bounded by 0 and 1. By using the inverse of the logit, we can eas-  
 356 ily transform our linear coefficients to obtain average effects on the scale of the proportions or percentages,  
 357 which is usually what is interesting to applied researchers. In a simple case, we can do this manually, but  
 358 when there are many factors in your model this can be quite complex.

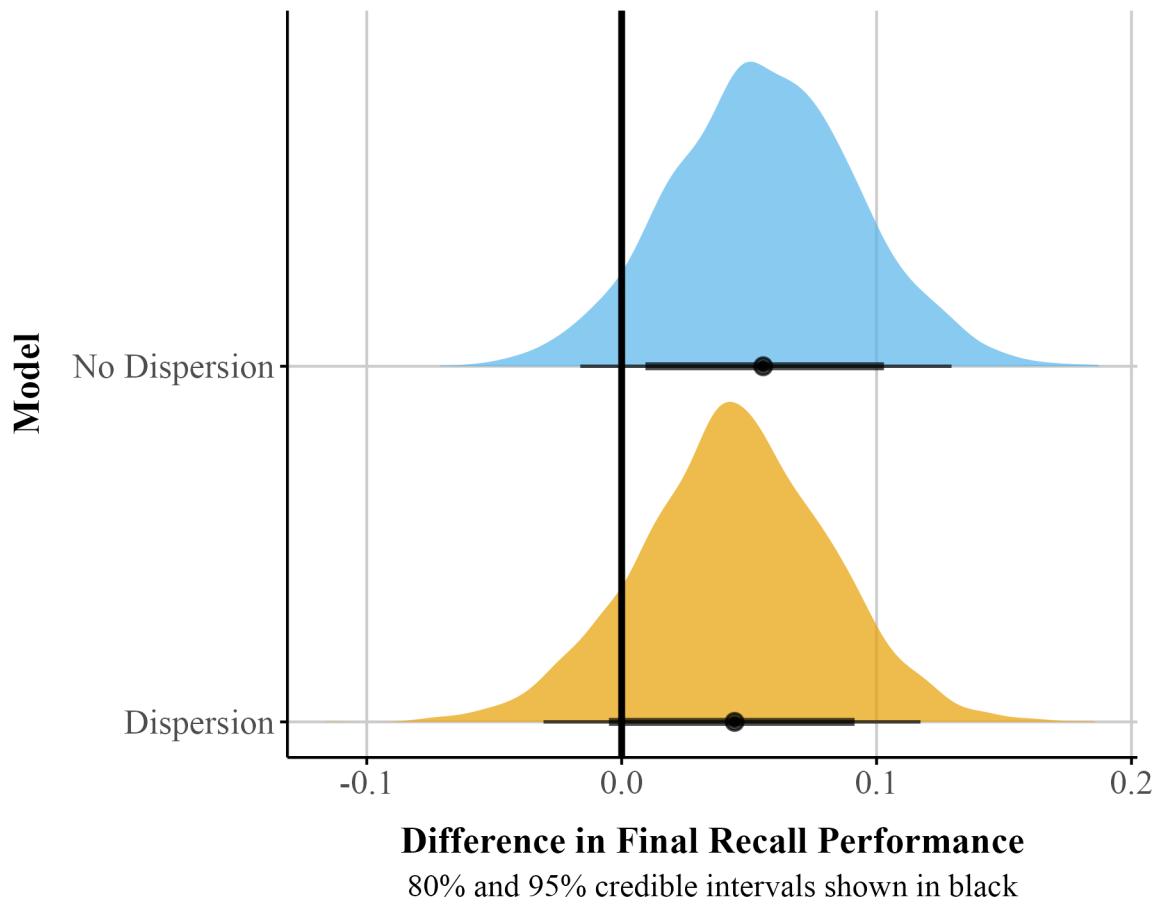
359 In our example, we can use the `plogis()` function in base R to convert estimates from the logit scale  
 360 to the probability scale. The intercept of our model is -0.918, which reflects the logit of the mean accuracy  
 361 in the disfluent condition. If the estimated difference between the fluent and disfluent conditions is 0.24 on  
 362 the logit scale, we first add this value to the intercept value (-0.918) to get the logit for the fluent condition:

---

<sup>7</sup>The model fit statistic LOO-CV can be compared for any set of fitted `brms` models with the function `loo()`.

**Figure 6**

*Comparison of posterior distributions for the risk difference in fluency: Simple model (no dispersion for Fluency) vs. complex model with dispersion*



363  $-0.83 + 0.20 = -0.63$ . We then use `plogis()` to convert both logit values to probabilities (Fluent =  
 364 35%, Disfluent = 30%).

365 With single coefficients this calculation is trivial, but in more complex models with interactions,  
 366 it can be quite cumbersome. To help us extract predictions from our model and visualize them we will  
 367 use a package called `{marginaleffects}` (Arel-Bundock et al., 2024) (see Listing 8). To get the proportions  
 368 for each of our categorical predictors on the  $\mu$  parameter we can use the function from the package called  
 369 `predictions()`. These are displayed in Table 2. These probabilities match what we calculated above.

---

**Listing 8** Load the `{marginaleffects}` package.
 

---

```
library(marginaleffects)
options(marginaleffects_posterior_center = mean) # make sure returns mean
```

---

370 For the Fluency factor, we can interpret Mean as proportions or percentages. That is, participants  
 371 who watched the fluent instructor scored on average 35% on the final exam compared to 30% for  
 372 those who watched the disfluent instructor. We can also visualize these from `{marginaleffects}` using the

---

**Listing 9** Predictions from the beta model for each level of Fluency.

---

```
predictions(
  beta_brms,
  # need to specify the levels of the categorical predictor
  newdata = datagrid(Fluency = c("Disfluent", "Fluent"))
)
```

---

**Table 2***Predicted probabilities for fluency factor.*

Fluency	Mean	95% Cr.I
Disfluent	0.297	[0.248, 0.348]
Fluent	0.353	[0.301, 0.41]

373 `plot_predictions()` function (see Listing 10).

---

**Listing 10** Plot predicted probabilities using `plot_predictions()` from `{marginaleffects}`

---

```
beta_plot <- plot_predictions(beta_brms, by = "Fluency")
```

---

374       The `plot_predictions()` function will only display the point estimate with the 95% credible interval. However, Bayesian estimation methods generate distributions for each parameter. This approach allows  
 375 visualizing full uncertainty estimates beyond points and intervals. Using the `{marginaleffects}` package, we  
 376 can obtain samples from the posterior distribution with the `posterior_draws()` function (see Listing 11).  
 377 We can then plot these results to illustrate the range of plausible values for our estimates at different levels  
 378 of uncertainty (see Figure 7).

---

**Listing 11** Extracting posterior draws from the beta regression model.

---

```
# Add a model identifier to each dataset
pred_draws_beta <- avg_predictions(beta_brms, variables = "Fluency") |>
  posterior_draws()
```

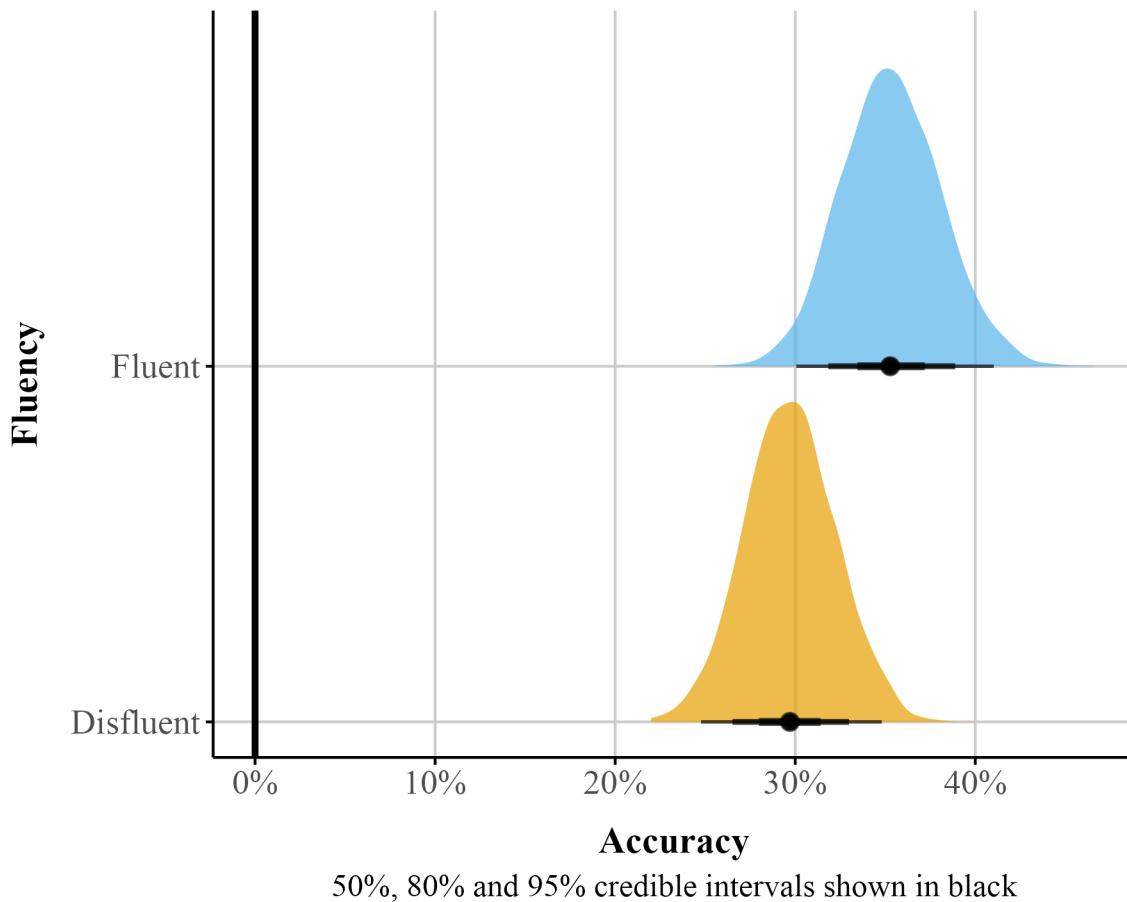
---

380 **Marginal Effects**

381       Marginal effects offer an interpretable way to quantify how changes in a predictor influence an outcome, while holding other factors constant in a specific manner. In recent years, there has been a thrust to  
 382 move away from reporting regression coefficients alone, focusing instead on estimates that are easier to interpret and communicate—particularly in non-linear models (McCabe et al., 2021; Rohrer & Arel-Bundock,  
 383 2025). Technically, marginal effects are computed as partial derivatives for continuous variables or as finite  
 384 differences for categorical (and sometimes continuous) predictors, depending on the structure of the data and  
 385 the research question. Substantively, these procedures translate raw regression coefficients into quantities  
 386 that reflect changes in the bounded outcome—for example, an  $x\%$  change in the value of a proportion.  
 387

**Figure 7**

*Predicted probability posterior distributions by fluency*



50%, 80% and 95% credible intervals shown in black

**Table 3**

*Fluency difference*

389 There are various types of marginal effects, and their calculation can vary across software packages.

390 For example, the popular `{emmeans}` package (Lenth, 2025) computes marginal effects by holding all pre-  
391 dictors at their means (MEM). In this tutorial, we will use the `{marginaleffects}` package (Arel-Bundock et  
392 al., 2024), which focuses on average marginal effects (AMEs) by default. AMEs summarize effects by gen-  
393 erating predictions for each row of the original dataset and then averaging these predictions. This approach  
394 retains a strong connection to the original data while offering a straightforward summary of the effect of  
395 interest.

396 One practical use of AMEs is to estimate the average difference between two groups or conditions

397 which corresponds to the average treatment effect (ATE). Using the `avg_comparisons()` function in the  
398 `{marginaleffects}` package (Listing 12), we can compute this quantity directly. By default, the function returns  
399 the discrete difference between groups. When we take the difference in proportions between two groups it  
400 is called the risk difference. Depending on the audience and modeling goals, the function can also produce  
401 alternative effect size metrics, such as odds ratios or risk ratios. This flexibility makes it a powerful approach  
402 for summarizing and communicating regression results.

---

**Listing 12** Calculating the difference between probabilities with `avg_comparisons()`

---

```
# get risk difference by default
beta_avg_comp <- avg_comparisons(beta_brms, comparison = "difference")
```

---

403       Table 3 presents the estimated difference for the Fluency factor (Mean column). The difference  
 404      between the fluent and disfluent conditions is 0.06, indicating that participants who watched a fluent instructor  
 405      scored, on average, 6% higher on the final recall test than those who watched a disfluent instructor. However,  
 406      the 95% credible interval includes 0 among the most credible values, suggesting we cannot rule out the  
 407      possibility of a null or weakly negative effect.

408       We can also use `{marginaleffects}` to get the actual precision difference between the two groups on  
 409       $\phi$  using similar code to above by setting `dpar` to “phi” {Listing 13}.

---

**Listing 13** Calculating  $\phi$  difference with `avg_comparisons()`

---

```
# get risk difference by default

beta_avg_phi <- avg_comparisons(
  beta_brms_dis,
  dpar = "phi",
  comparison = "difference"
)
```

---

410       In psychology, it is common to report effect size measures like Cohen’s  $d$  (Cohen, 1977). When  
 411      working with proportions we can calculate something similar called Cohen’s  $h$ . Taking our proportions, we  
 412      can use the below equation (Equation 2) to calculate Cohen’s  $h$  along with the 95% Cr.I around it. Using this  
 413      metric we see the effect size is small (0.107), 95% credible interval [-0.002, 0.361].

$$h = 2 \cdot (\arcsin(\sqrt{p_1}) - \arcsin(\sqrt{p_2})) \quad (2)$$

414       **Posterior Predictive Check**

415       Figure 12 (B) shows the predictive check for our beta model. The model’s predictions generally  
 416      conform to the data as the predictions are now between constrained to the 0-1 interval. However, we can  
 417      further improve the model’s predictive performance if we take into account the bounds of the scale more  
 418      explicitly.

419       **Zero-Inflated beta (ZIB) Regression**

420       A limitation of the beta regression model is that it can only accommodate values strictly between  
 421      0 and 1—a probability cannot take on values of 0 (the event will not occur with certainty) or 1 (the event  
 422      will occur with certainty). In our dataset, we observed 9 rows where Accuracy equals zero. To fit a beta  
 423      regression model, we removed these values, but we have left out potentially valuable information from our  
 424      model—especially if the end points of the scale are distinctive in some way. In our case, these 0s may be  
 425      structural—that is, they represent real, systematic instances where participants failed to answer correctly  
 426      (rather than random noise or measurement error). For example, the fluency of the instructor might be a  
 427      key factor in predicting these zero responses. We will discuss two approaches for jointly modeling these end

428 points with the continuous data. First, we can use a zero-inflated beta (ZIB) model. This model still estimates  
 429 the mean ( $\mu$ ) and precision ( $\phi$ ) of the beta distribution for values between 0 and 1, but it also includes an  
 430 additional parameter,  $\alpha$ , which captures the probability of observing structural 0s.

431 The zero-inflated beta models a mixture of the data-generating process. The  $\alpha$  parameter uses a  
 432 logistic regression to model whether the data is 0 or not. Substantively, this could be a useful model when we  
 433 think that 0s come from a process that is relatively distinct from the data that is greater than 0. For example,  
 434 if we had a dataset with proportion of looks or eye fixations to certain areas on marketing materials, we might  
 435 want a separate model for those that do not look at certain areas on the screen because individuals who do  
 436 not look might be substantively different than those that look.

437 We can fit a ZIB model using `brms()` and use the `{marginaleffects}` package to make inferences  
 438 about our parameters of interest. Before we run a zero-inflated beta model, we will need to transform our  
 439 data again and remove the one 1 value in our data—we can keep our 0s. Similar to our beta regression model  
 440 we fit in `brms`, we will use the `bf()` function to fit several models. We fit our  $\mu$  and  $\phi$  parameters as well as  
 441 our zero-inflated parameter ( $\alpha$ ; here labeled as `zi`). In `brms` we can use the `zero_inflated_beta` family (see  
 442 Listing 14).

---

**Listing 14** Fitting zib model with `brm()`


---

```
# keep 0 but remove 1
data_beta_0 <- fluency_data |>
  filter(Accuracy != 1)

# set up model formual for zero-inflated beta in brm
zib_model <- bf(
  Accuracy ~ Fluency, # The mean of the 0-1 values, or mu
  phi ~ Fluency, # The precision of the 0-1 values, or phi
  zi ~ Fluency, # The zero-or-one-inflated part, or alpha
  family = zero_inflated_beta()
)

# fit zib model with brm
fit_zi <- brm(
  formula = zib_model,
  data = data_beta_0,
  file = here::here("manuscript", "models", "bayes_zib_model0not1.rds")
)
```

---

443 **Posterior Predictive Check**

444 The ZIB model does a bit better at capturing the structure of the data than the beta regression model  
 445 (see Figure 12). Specifically, the ZIB model more accurately captures the increased density of values near  
 446 the lower end of the scale (i.e., near zero), which the standard beta model underestimates. The ZIB model's  
 447 predictive distributions also align more closely with the observed data across the entire range, particularly in  
 448 the peak and tail regions. This improved fit likely reflects the ZIB model's ability to explicitly model excess  
 449 0s (or near-zero values) via its inflation component, allowing it to better account for features in the data that  
 450 a standard beta distribution cannot accommodate.

**Table 4***Probability fluency difference ( $\mu$ )*

Contrast	Mean	95% Cr.I	pd
Fluent - Disfluent	0.044	[-0.031, 0.117]	0.881

**Table 5***Probability fluency difference ( $\phi$ )*

Contrast	Mean	95% Cr.I	pd
Fluent - Disfluent	2.7	[-0.94, 6.844]	0.928

451 **Predicted Probabilities and Marginal Effects**

452 Table 8, under the zero-inflated beta regression column, provides a summary of the posterior distribution  
 453 for each parameter. As stated before, it is preferable to back-transform our estimates to get probabilities.  
 454 To get the predicted probabilities we can again use the `avg_predictions()` and `avg_comparisons()`  
 455 functions from `{marginaleffects}` package (Arel-Bundock, 2024) to get predicted probabilities and the prob-  
 456 ability difference between the levels of each factor. We can model the parameters separately using the `dpar`  
 457 argument setting to:  $\mu$ ,  $\phi$ ,  $\alpha$ . Here we look at the risk difference for Fluency under each parameter. If one  
 458 were interested in the average effect for the entire model, the `dpar` argument could be removed.

459 **Mu.** As shown in Table 4, there is little evidence for an effect of Fluency – the 95% Cr.I includes  
 460 zero, suggesting substantial uncertainty about the direction and magnitude of the effect—that is, though most  
 461 of the posterior density supports positive effects, nil and weakly negative effects cannot be ruled out.

462 **Dispersion.** As shown in Table 5, the posterior estimates suggest a credible effect of Fluency on  
 463 dispersion ( $\phi$ ), with disfluent responses showing greater variability. The 95% Cr.I for the fluency contrast  
 464 does not include zero, indicating a high probability in differences in precision.

465 **Zero-Inflation**

466 We can use `{marginaleffects}` to estimate and plot the posterior difference between the fluent and  
 467 disfluent conditions (see Figure 8). In Figure 8, the posterior distribution for this contrast lies mostly below  
 468 zero, indicating that a fluent instructor is associated with a lower probability of zero responses. The estimated  
 469 reduction is approximately 13%. The 95% credible interval does not include zero, which indicates that the  
 470 data provide consistent evidence for a reduction in zero responses under fluent instruction.

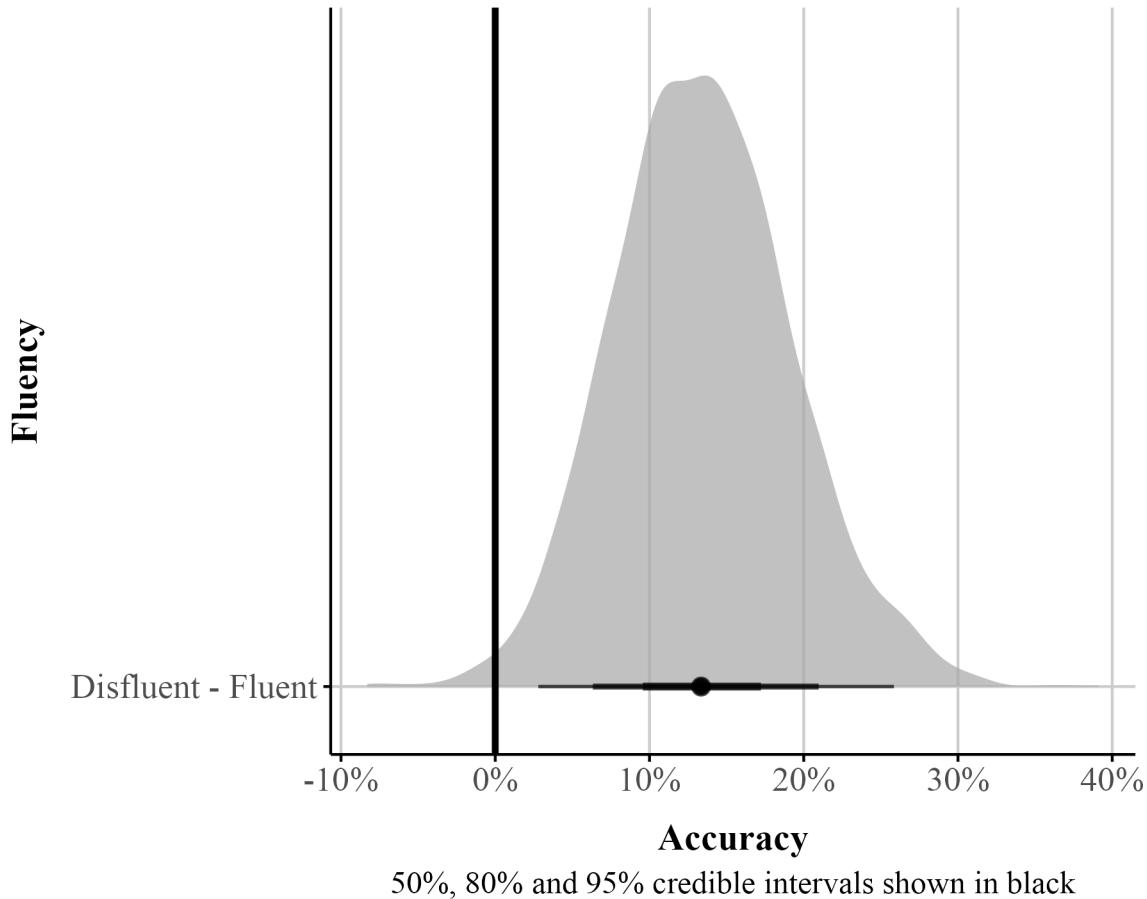
471 **Zero-One-Inflated beta (ZOIB)**

472 The ZIB model works well if there are 0s in your data, but not 1s.<sup>8</sup> In our previous examples we  
 473 either got rid of both 0s and 1s (beta regression), or removed the 1s (ZIB). Sometimes it is theoretically useful  
 474 to model both 0s and 1s as separate processes or to consider these values as essentially similar parts of the  
 475 continuous response, as we show later in the ordered beta regression model. For example, this is important  
 476 in visual analog scale data where there might be a prevalence of responses at the bounds (Kong & Edwards,

<sup>8</sup>In cases where your data include exact 1s but no 0s, you can fit a one-inflated beta regression model in `brms` by setting the `coi` parameter to 1. This tells the model that all point masses occur at 1, rather than being split between 0 and 1. In other words, `coi = 1` assumes that any inflation in the data is due entirely to values at 1. In our data, we have exactly one value equal to 1[<sup>6</sup>]. While probably not significant to alter our findings, we can model 1s with a special type of model called the zero-one-inflated beta (ZOIB) model (Liu & Kong, 2015) if we believe that both 0s and 1s are distinct outcomes.

**Figure 8**

*Visualization of the predicted difference for zero-inflated part of model*



477 2016), in JOL tasks (Wilford et al., 2020), or in a free-list task where individuals provide open responses to  
 478 some question or topic which are then recoded to fall between 0-1 (Bendixen & Purzycki, 2023). Here 0s  
 479 and 1s are meaningful; 0 means item was not listed and 1 means the item was listed first.

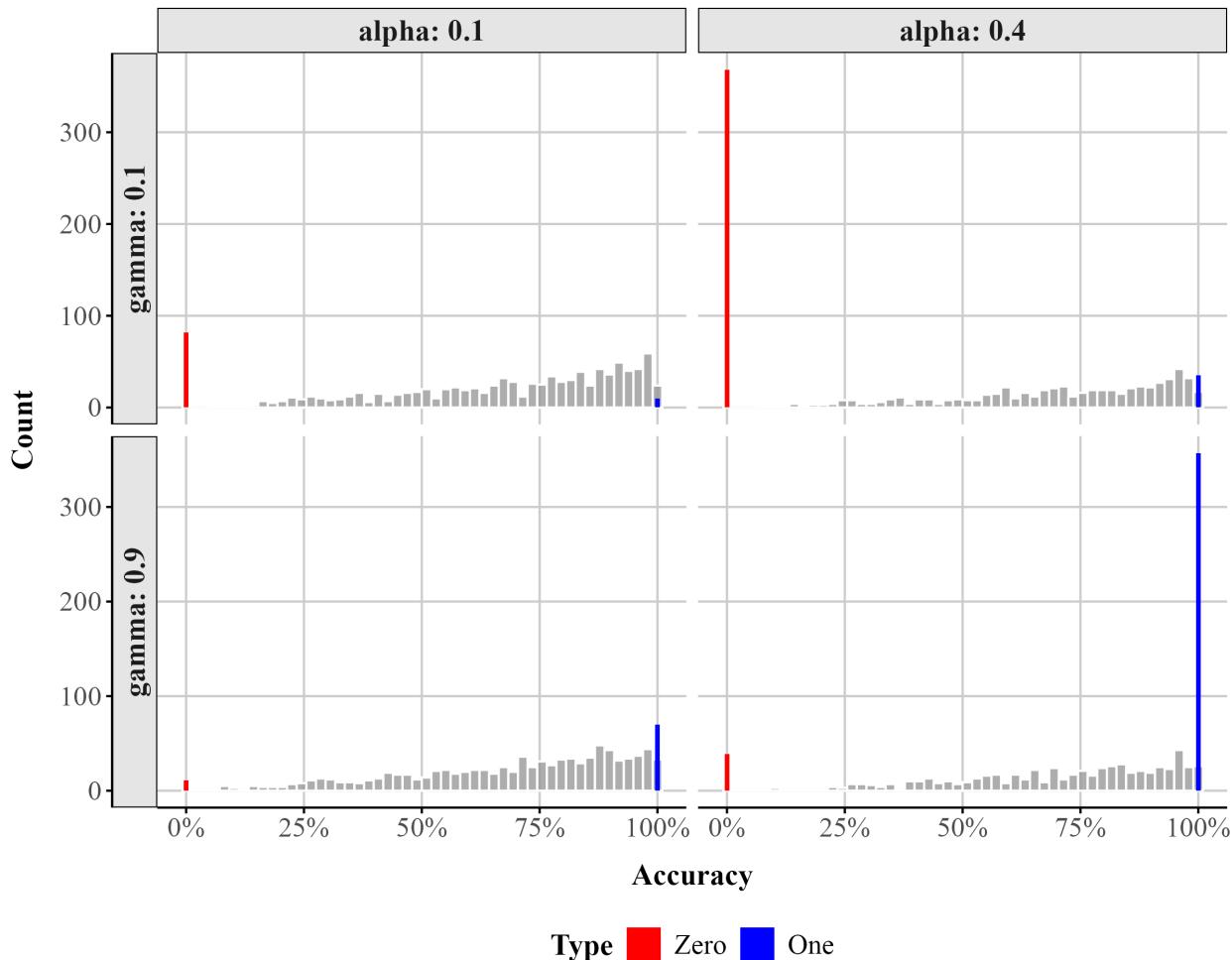
480 Similar to the beta and zero-inflated models discussed above, we can fit a zero-and-one-inflated beta  
 481 (ZOIB) model in `{brms}` using the `zero_one_inflated_beta` family. This formulation simultaneously  
 482 estimates the mean  $\mu$  and precision  $\phi$  of the Beta component, as well as two inflation parameters:  $\alpha$ , the  
 483 probability that an observation is at either boundary (0 or 1), and  $\gamma$ , the conditional probability that, given  
 484 an observation falls on a boundary, it takes the value 1 rather than 0. In other words,  $\alpha$  determines how often  
 485 responses occur exactly at the endpoints, and  $\gamma$  determines the balance between zeros and ones among those  
 486 endpoint values. This specification allows the model to capture both the continuous variation in the interior  
 487 of the (0, 1) interval and the presence of exact boundary values.

488 To illustrate how  $\alpha$  and  $\gamma$  shape the distribution, Figure 9 displays simulated data across a range  
 489 of parameter combinations. As  $\alpha$  increases, more responses occur at the endpoints. As  $\gamma$  increases, the  
 490 proportion of those endpoint responses that are 1 increases relative to 0, producing increasingly pronounced  
 491 spikes at 1 as  $\gamma$  approaches 1. Together, these parameters give the ZOIB model the flexibility to represent  
 492 datasets with mixtures of continuous values and exact zeros and ones.

493 To fit a ZOIB model we use the `bf()` function. We model each parameter as a function of Fluency.  
 494 We then pass the `zoib_model` to our `brm()` function (see Listing 15). The summary of the output is in

**Figure 9**

*Simulated data from a ZOIB model illustrating the effects of the zero-one inflation parameter ( $\alpha$ ) and the conditional one-inflation parameter ( $\gamma$ ).*



495 Table 8 (under ZOIB).

496 **Model Parameters**

497 The output for the model is lengthy because we are estimating four distinct components, each with  
 498 their own independent responses and sub-models. All the coefficients are on the logit scale, except  $\phi$ , which is  
 499 on the log scale. Thankfully drawing inferences for all these different parameters, plotting their distributions,  
 500 and estimating their average marginal effects looks exactly the same—all the brms and {marginaleffects}  
 501 functions we used work the same.

502 **Predictions and Marginal Effects**

503 With {marginaleffects} we can choose marginalize over all the sub-models, averaged across the 0s,  
 504 continuous responses, and 1s in the data, or we can model the parameters separately using the dpar argument  
 505 like we did above setting it to:  $\mu$ ,  $\phi$ ,  $\alpha$ ,  $\gamma$  (see below). Using avg\_predictions() and not setting dpar we  
 506 can get the predicted probabilities across all the sub-models. We can also plot the overall difference between

---

**Listing 15** Fitting a ZOIB model with `brm()`.

```
# fit the zoib model

zoib_model <- bf(
  Accuracy ~ Fluency, # The mean of the 0-1 values, or mu
  phi ~ Fluency, # The precision of the 0-1 values, or phi
  zoi ~ Fluency, # The zero-or-one-inflated part, or alpha
  coi ~ Fluency, # The one-inflated part, conditional on the 1s, or gamma
  family = zero_one_inflated_beta()
)

fit_zoib <- brm(
  formula = zoib_model,
  data = fluency_data,
  file = here::here("manuscript", "models", "bayes_zoib_model")
)
```

---

507 fluency and disfluency for the whole model with `plot_predictions()`.

508 In addition, we show below how one can extract the predicted probabilities and marginal effects for  
509  $\gamma$  (and a similar process for any other model component, `zoi`, etc.):

---

**Listing 16** Extracting predicted probabilities and marginal effects for conditional-one parameter

```
# get average predictions for coi param
coi_probs <- avg_predictions(fit_zoib, by = c("Fluency"), dpar = "coi")
# get difference between the two conditions
coi_me <- avg_comparisons(fit_zoib, variables = c("Fluency"), dpar = "coi")
```

---

510 **Ordered Beta Regression**

511 Looking at the output from the ZOIB model (Table 8), we can see how running a model like this  
512 can become fairly complex as it is fitting distinct sub-models for each component of the scale. The ability  
513 to consider 0s and 1s as distinct processes from continuous values comes at a price in terms of complexity  
514 and interpretability. A simplified version of the zero-one-inflated beta (ZOIB) model, known as ordered  
515 beta regression (Kubinec, 2022; see also Makowski et al., 2025 for a reparameterized version called the  
516 *beta-Gate* model), has been recently proposed. The ordered beta regression model exploits the fact that,  
517 for most analyses, the continuous values (between 0-1) and the discrete outcomes (e.g., 0 or 1) are *ordered*.  
518 For example, as a covariate  $x$  increases or decreases, we should expect the bounded outcome  $y$  to increase  
519 or decrease monotonically as well from 0 to (0, 1) to 1. The ZOIB model does not impose this restriction;  
520 a covariate could increase and the response  $y$  could increase in its continuous values while *simultaneously*  
521 decreasing at *both* end points.<sup>9</sup> This complexity is not immediately obvious when fitting the ZOIB, nor is  
522 it a potential relationship that many scholars want to consider when examining how covariates influence a  
523 bounded scale.

---

<sup>9</sup>For a more complete description of this issue, we refer the reader to Kubinec (2022).

524 To make the response ordered, the ordered beta regression model estimates a weighted combination  
 525 of a standard beta regression model for continuous responses and a logit model for the discrete values of  
 526 the response. By doing so, the amount of distinctiveness between the continuous responses and the discrete  
 527 end points is a function of the data (and any informative priors) rather than strictly defined as fully distinct  
 528 processes as in the ZOIB. For some datasets, the continuous and discrete responses will be fairly distinct,  
 529 and in others less so.

530 The weights that average together the two parts of the outcome (i.e., discrete and continuous) are  
 531 determined by cutpoints that are estimated in conjunction with the data in a similar manner to what is known  
 532 as an ordered logit model. An in-depth explanation of ordinal regression is beyond the scope of this tutorial  
 533 (Bürkner & Vuorre, 2019; but see Fullerton & Anderson, 2021). At a basic level, ordinal regression models  
 534 are useful for outcome variables that are categorical in nature and have some inherent ordering (e.g., Likert  
 535 scale items). To preserve this ordering, ordinal models rely on the cumulative probability distribution.  
 536 Within an ordinal regression model it is assumed that there is a continuous but unobserved latent variable  
 537 that determines which of  $k$  ordinal responses will be selected. For example on a typical Likert scale from  
 538 ‘Strongly Disagree’ to ‘Strongly Agree’, you could assume that there is a continuous, unobserved variable  
 539 called ‘Agreement’.

540 While we cannot measure Agreement directly, the ordinal response gives us some indication about  
 541 where participants are on the continuous Agreement scale.  $k - 1$  cutoffs are then estimated to indicate the  
 542 point on the continuous Agreement scale at which your Agreement level is high enough to push you into the  
 543 next ordinal category (say Agree to Strongly Agree). Coefficients in the model estimate how much differ-  
 544 ent predictors change the estimated *continuous* scale (here, Agreement). Since there’s only one underlying  
 545 process, there’s only one set of coefficients to work with (proportional odds assumption). In an ordered beta  
 546 regression, three ordered categories are modeled: (1) exactly zero, (2) somewhere between zero and one,  
 547 and (3) exactly one. In an ordered beta regression, (1) and (2) are modeled with cumulative logits, where  
 548 one cutpoint is the the boundary between Exactly 0 and Between 0 and 1 and the other cutpoint is the bound-  
 549 ary between *Between 0 and 1* and *Exactly 1*. The continuous values in the middle, 0 to 1 (3), are modeled  
 550 as a vanilla beta regression with parameters reflecting the mean response on the logit scale as we have de-  
 551 scribed previously. Ultimately, employing cutpoints allows for a smooth transition between the bounds and  
 552 the continuous values, permitting both to be considered together rather than modeled separately as the ZOIB  
 553 requires.

554 The ordered beta regression model has shown to be more efficient and less biased than some of the  
 555 methods discussed (Kubinec, 2022) herein and has seen increasing use across the biomedical and social  
 556 sciences (Martin et al., 2024; Nouvian et al., 2023; Shrestha et al., 2024; Smith et al., 2024; Wilkes et al.,  
 557 2024) because it produces only a single set of coefficient estimates in a similar manner to a standard beta  
 558 regression or OLS.<sup>10</sup>

### 559 ***Fitting an Ordered Beta Regression***

560 To fit an ordered beta regression in a Bayesian context we use the `{ordbetareg}` (Kubinec, 2023) pack-  
 561 age. `{ordbetareg}` is a front-end to the `brms` package that we described earlier; in addition to the functions  
 562 available in the package, most `brms` functions and plots, including the diverse array of regression model-  
 563 ing options, will work with `{ordbetareg}` models. (We note that the `ordbeta` model is also available as a  
 564 maximum-likelihood variant in the R package `{glmmTMB}`.) We first load the `{ordbetareg}` package (see  
 565 Listing 17).

566 The `{ordbetareg}` package uses `brms` on the front-end so all the arguments we used previously apply  
 567 here. Instead of the `brm()` function we use `ordbetareg()`. To fit a model where dispersion does not vary

---

<sup>10</sup>Please note that there are other models available that can model this continuous process like the beta-gate model (Makowski et al., 2025) and the censored extended beta regression model (Kosmidis & Zeileis, 2025).

---

**Listing 17** Load {ordbetareg}

```
library(ordbetareg)
```

---

**Table 6***Marginal effect of fluency ordered beta model*

Contrast	Mean	95% Cr.I	pd
Fluent - Disfluent	0.061	[-0.015, 0.137]	0.938

---

568 as a function of fluency we can use the below code (see Listing 18).

---

**Listing 18** Fitting ordered beta model with ordbetareg()

```
ord_fit_brms <- ordbetareg(
  Accuracy ~ Fluency,
  data = fluency_data,
  file = here::here("manuscript", "models", "bayes_ordbeta_model")
)
```

---

569 However, if we want dispersion to vary as a function of fluency we can easily do that (see Listing 19).  
 570 Note the addition of the `phi_reg` argument in `m.phi`. This argument allows us to include a model that  
 571 explicitly models the dispersion parameter. Because we are modeling  $\phi$  as a function of fluency, we set the  
 572 the argument to `both`.

---

**Listing 19** Fitting ordered beta model with dispersion using ordbetareg()

```
ord_beta_phi <- bf(Accuracy ~ Fluency, phi ~ Fluency)

m.phi <- ordbetareg(
  ord_beta_phi,
  data = fluency_data,
  phi_reg = 'both',
  file = here::here("manuscript", "models", "bayes_ordbeta_phi_model")
)
```

---

573 **Marginal Effects.** Table 8 presents the posterior summary. We can use `{marginaleffects}` to calculate differences on the response scale that average over (or marginalize over) all our parameters.  
 574

575 In Table 6 the credible interval is close enough to zero relative to its uncertainty that we can conclude  
 576 there likely aren't differences between the conditions after taking dispersion and the 0s and 1s in our data  
 577 into account.

578 **Cutpoints.** The model cutpoints are not reported by default in the summary output, but we can access them with the R package `posterior` (Bürkner et al., 2025) and the functions `as_draws` and  
 579 `summary_draws`.

**Table 7**

*Cutzero and cutone parameter summary*

Parameter	Mean	95% Cr.I
cutzero	-2.97	[-3.58, -2.41]
cutone	1.85	[1.63, 2.08]

581 In Table 7, `cutzero` is the first cutpoint (the difference between 0 and continuous values) and `cutone`  
 582 is the second cutpoint (the difference between the continuous values and 1). These cutpoints are on the  
 583 logit scale and as such the numbers do not have a simple substantive meaning. In general, as the cutpoints  
 584 increase in absolute value (away from zero), then the discrete/boundary observations are more distinct from  
 585 the continuous values. This will happen if there is a clear gap or bunching in the outcome around the bounds.  
 586 This type of empirical feature of the distribution may be useful to scholars if they want to study differences  
 587 in how people perceive the ends of the scale versus the middle. It is possible, though beyond the scope of  
 588 this article, to model the location of the cutpoints with hierarchical (non-linear) covariates in `brms`. In the  
 589 most recent version of `ordbeta`, it is possible to test the influence of different factors on these boundaries.

### 590 **Model Fit**

591 The best way to visualize model fit is to plot the full predictive distribution relative to the original  
 592 outcome. Because ordered beta regression is a mixed discrete/continuous model, a separate plotting function,  
 593 `pp_check_ordbetareg`, is included in the `{ordbetareg}` package that accurately handles the unique features  
 594 of this distribution. The default plot in `brms` will collapse these two features of the outcome together, which  
 595 will make the fit look worse than it actually is. The `{ordbetareg}` function returns a list with two plots,  
 596 `discrete` and `continuous`, which can either be printed and plotted or further modified as `{ggplot2}` objects  
 597 (see Figure 10).

598 The discrete plot, which is a bar graph, shows that the posterior distribution accurately captures the  
 599 number of different types of responses (discrete or continuous) in the data. For the continuous plot shown as  
 600 a density plot with one line per posterior draw, the model does a very good job at capturing the distribution.

601 Overall, it is clear from the posterior distribution plot that the ordered beta model fits the data well.  
 602 To fully understand model fit, both of these plots need to be inspected as they are conceptually distinct.

### 603 **Model Visualization**

604 `{ordbetareg}` provides a useful visualization function called `plot_heiss()` (Ye & Heiss, 2023) that  
 605 can represent dispersion in the entire outcome as a function of discrete covariates. This function produces a  
 606 plot of predicted proportions across the range of our Fluency factor. In Figure 11 we get predicted propor-  
 607 tions for Fluency across the bounded scale. Looking at the figure we can see there is much overlap between  
 608 instructors in the middle portion ( $\mu$ ). However, we do see some small differences at the zero bounds.

### 609 **Ordered Beta Scale**

610 In the `{ordbetareg}` function there is a `true_bound` argument. In cases where your data is not  
 611 bounded between 0-1, this argument can be used to specify the bounds of the argument to fit the ordered  
 612 beta regression. For example, the response data might be bounded between 1 and 7. If so, `{ordbetareg}` can  
 613 model it within the [0,1] interval and `{ordbetareg}` will convert the model predictions back to the true bounds  
 614 after estimation.

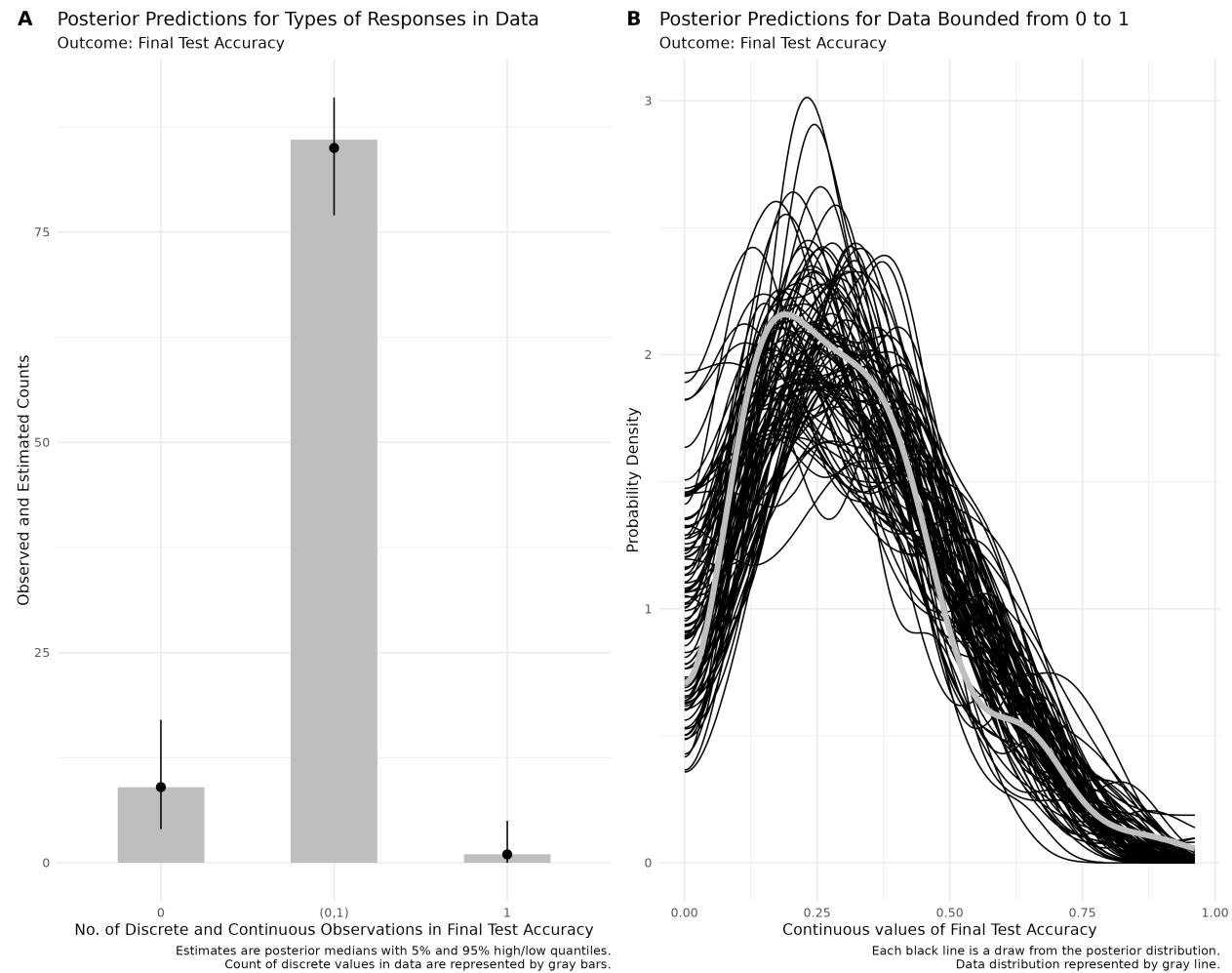
**Table 8***Bayesian regression summaries for each model*

Parameter	Stat	Bayesian LM	Beta Regression	ZIB	ZOIB	Ordered Beta
b_Intercept	Mean	0.257	-0.830	-0.831	-0.830	-0.867
	Cr.I	[0.202, 0.316]	[-1.103, -0.562]	[-1.094, -0.566]	[-1.094, -0.573]	[-1.122, -0.613]
	pd	1.000***	1.000***	1.000***	1.000***	1.000***
b_Fluency	Mean	0.084	0.202	0.204	0.202	0.260
	Cr.I	[0, 0.168]	[-0.139, 0.543]	[-0.138, 0.545]	[-0.136, 0.558]	[-0.064, 0.589]
	pd	0.976*	0.880	0.881	0.875	0.938
sigma	Mean	0.208	-	-	-	-
	Cr.I	[0.181, 0.242]	-	-	-	-
	pd	1.000***	-	-	-	-
b_phi_Intercept	Mean	-	1.602	1.597	1.605	1.620
	Cr.I	-	[1.169, 1.985]	[1.183, 1.998]	[1.197, 1.983]	[1.221, 2.004]
	pd	-	1.000***	1.000***	1.000***	1.000***
b_phi_Fluency	Mean	-	0.422	0.429	0.418	0.401
	Cr.I	-	[-0.138, 0.983]	[-0.149, 1.014]	[-0.145, 0.967]	[-0.192, 0.971]
	pd	-	0.930	0.928	0.926	0.910
b_zi_Intercept	Mean	-	-	-1.659	-	-
	Cr.I	-	-	[-2.509, -0.953]	-	-
	pd	-	-	1.000***	-	-
b_zi_Fluency	Mean	-	-	-2.123	-	-
	Cr.I	-	-	[-4.532, -0.347]	-	-
	pd	-	-	0.992**	-	-
b_zoi_Intercept	Mean	-	-	-	-1.549	-
	Cr.I	-	-	-	[-2.345, -0.861]	-
	pd	-	-	-	1.000***	-
b_zoi_Fluency	Mean	-	-	-	-2.231	-
	Cr.I	-	-	-	[-4.749, -0.463]	-
	pd	-	-	-	0.997***	-
b_coi_Intercept	Mean	-	-	-	-2.068	-
	Cr.I	-	-	-	[-4.429, -0.317]	-
	pd	-	-	-	0.993**	-
b_coi_Fluency	Mean	-	-	-	0.245	-
	Cr.I	-	-	-	[-6.448, 5.765]	-
	pd	-	-	-	0.563	-

Note. Link functions: b\_mean = logit; b\_phi = log; b\_zoi (zero-one inflation) = logit; b\_coi (conditional one-inflation) = logit. Asterisks reflect approximate two-sided p-values derived from the posterior pd. pd  $\geq 0.975$  ( $p \leq .05$ ) = \*; pd  $\geq 0.990$  ( $p \leq .01$ ) = \*\*; pd  $\geq 0.998$  ( $p \leq .001$ ) = \*\*\*.

**Figure 10**

*Posterior predictive check for ordered beta regression model. A. Discrete posterior check. B. Continuous posterior check.*



615

## Discussion

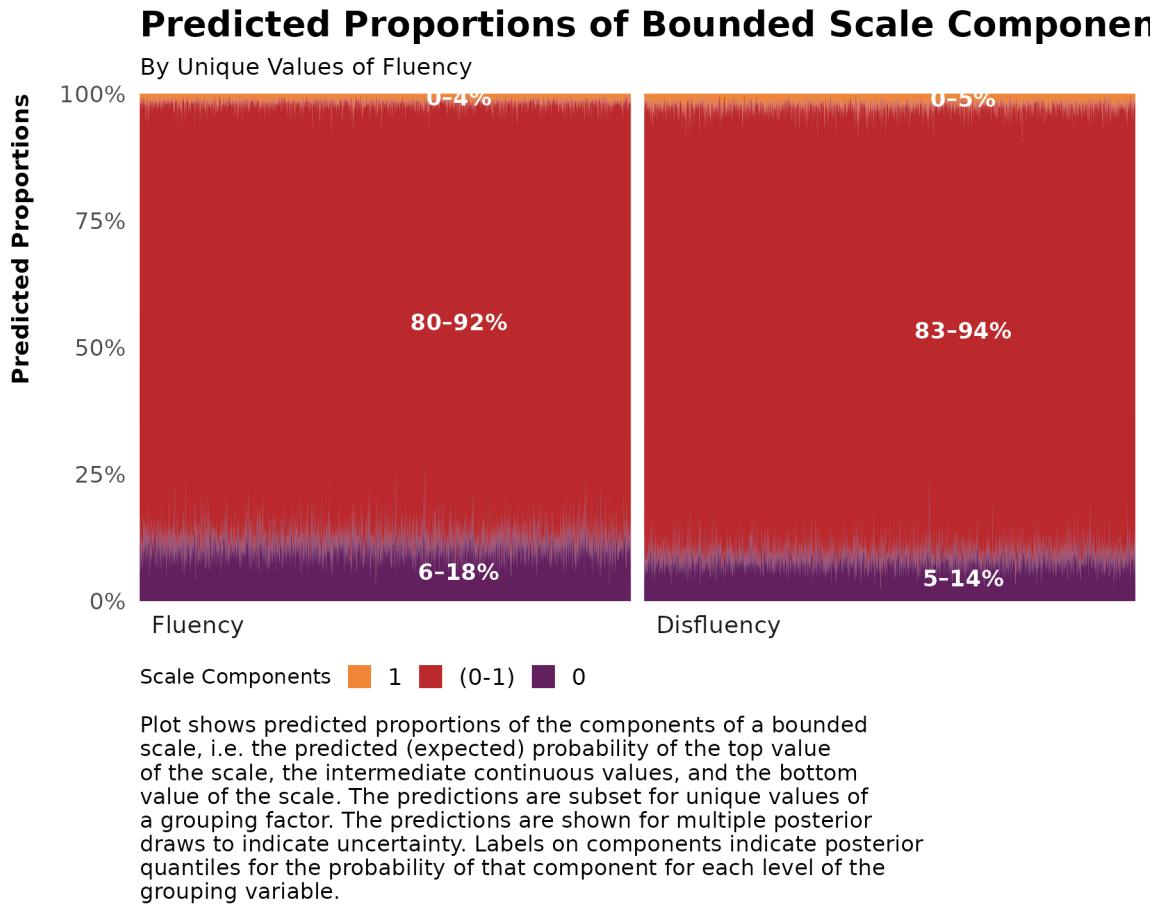
616       The use of beta regression in psychology, and the social sciences in general, is rare. With this tutorial,  
 617       we hope to turn the tides. Beta regression models are an attractive alternative to models that impose un-  
 618       realistic assumptions like normality, linearity, homoscedasticity, and unbounded data. Beyond these models,  
 619       there are a diverse array of different models that can be used depending on your outcome of interest.

620       Throughout this tutorial our main aim was to help guide researchers in running analyses with pro-  
 621       portional or percentage outcomes using beta regression and some of its alternatives. In the current example,  
 622       we used real data from Wilford et al. (2020) and discussed how to fit these models in R, interpret model  
 623       parameters, extract predicted probabilities and marginal effects, and visualize the results.

624       Comparing our analysis with that of Wilford et al. (2020), we demonstrated that using a traditional  
 625       approache (e.g.,  $t$ -test) to analyze mean accuracy data can lead to biased inferences. Although we successfully  
 626       reproduced one of their key findings, our use of beta regression and its extensions revealed important nuances  
 627       in the results. With a traditional beta regression model—which accounts for both the mean and the precision  
 628       (dispersion)—we observed similar effects of instructor fluency on performance. However, the standard beta

**Figure 11**

*Heiss plot of predicted probabilities across the scale (0-100)*



model does not accommodate boundary values (i.e., 0s and 1s).

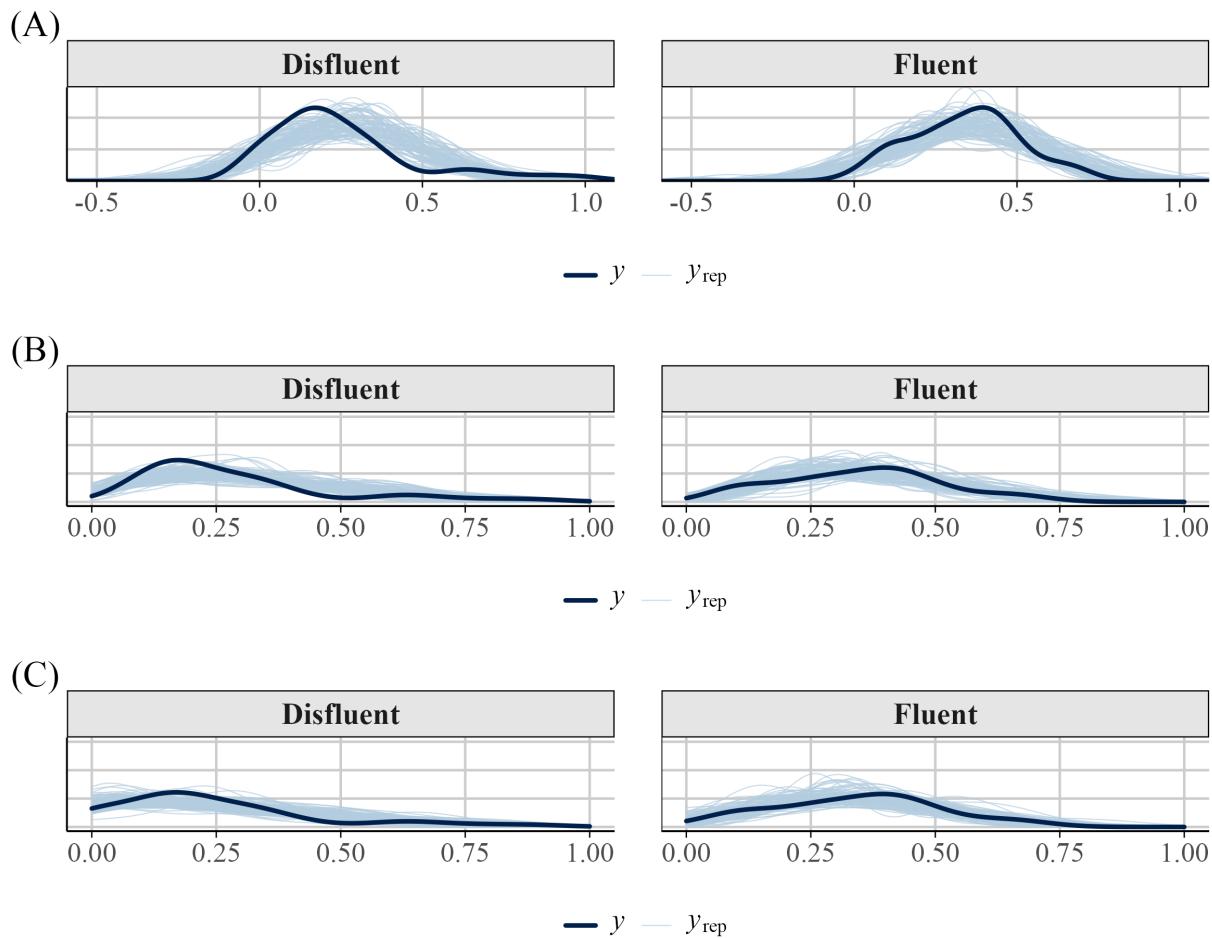
When we applied a ZIB model, which explicitly accounts for structural 0s, we found no effect of fluency on the mean ( $\mu$ ) part of the model. Instead, the effect of fluency emerged in the structural zero (inflated zero;  $\alpha$ ) component. This pattern was consistent when using a zero-one-inflated beta (ZOIB) model. Furthermore, we fit an ordered beta regression model (Kubinec, 2022), which appropriately models the full range of values, including 0s and 1s. Here, we did not observe a reliable effect of fluency on the mean once we accounted for dispersion.

These analyses emphasize the importance of fitting a model that aligns with the nature of the data. The simplest and recommended approach when dealing with data that contains 0s and/or 1s is to fit an ordered beta model, assuming the process is truly continuous. However, if you believe the process is distinct in nature, a ZIB or ZOIB model might be a better choice. Ultimately, this decision should be guided by theory.

For instance, if we believe fluency influences the boundaries (0 and 1), we might want to model this process separately using a ZIB or ZOIB. With the current dataset, fluency might affect specific aspects of performance (such as the likelihood of complete failure) rather than general performance levels. This effect could be due to participant disengagement during the disfluent lecture. If students fail to pay attention because of features of disfluency, they may miss relevant information, leading to a floor effect at the test. Following from this, disfluency would be expected to influence the boundary (0) and not the continuous part of the model. If this is the case, we would want to model this appropriately. However, if we believe fluency

**Figure 12**

The plots show 100 posterior predicted distributions with the label  $y_{rep}$  (light blue), the distribution of accuracy as function of fluency in dark blue for regular regression (A), beta regression (B), and ZIB (C) models



647 effects general performance levels (the continuous part), a model that takes in to account the entire process  
 648 accounting for the 0s and 1s might be appropriate.

649 In the discussion section of Wilford et al. (2020), they were unable to offer a tenable explanation for  
 650 performance differences based on instructor fluency. A model that accounts for the excess 0s in the dataset  
 651 provides one testable explanation: watching a disfluent lecture may lead to lapses in attention, resulting  
 652 in poorer performance in that group. These lapses, in turn, contribute to the observed differences in the  
 653 fluent condition. This modeling approach opens a promising avenue for future research—one that would have  
 654 remained inaccessible otherwise.

655 Not everyone will be eager to implement the techniques discussed herein. In such cases, the key  
 656 question becomes: What is the least problematic approach to handling proportional data? One reasonable  
 657 option is to fit multiple models tailored to the specific characteristics of your data. For example, if your data  
 658 contain 0s, you might fit two models: a traditional linear model excluding the 0s, and a logistic model to  
 659 account for the zero versus non-zero distinction. If your data contain both 0s and 1s, you could fit separate  
 660 models for the 0s and 1s in addition to the OLS model. There are many defensible strategies to choose from  
 661 depending on the context. However, we do not recommend transforming the values of your data (e.g., 0s to

662 .01 and 1s to .99) or ignoring the properties of your data simply to fit traditional statistical models.

663 In this tutorial, we demonstrated how to analyze these models from a Bayesian perspective. While we  
664 recognize that not everyone identifies as a Bayesian, implementing these models using a Bayesian framework  
665 is relatively straightforward—it requires only a single package, lowering the barrier to entry. For those who  
666 prefer frequentist analyses, several R packages are available. For example, the `{betareg}` package (Cribari-  
667 Neto & Zeileis, 2010) `{glmmTMB}` (Brooks et al., 2017) and `{gamlss}` (2005) are nice options. To this end,  
668 I have included supplemental materials demonstrating how to use frequentist packages to analyze the data  
669 presented herein.

## 670 Conclusion

671 Overall, this tutorial emphasizes the importance of modeling the data you have. Although the ex-  
672 ample provided is relatively simple (a one-factor model with two levels), we hope it demonstrates that even  
673 with a basic dataset, there is much nuance in interpretation and inference. Properly modeling your data  
674 can lead to deeper insights, far beyond what traditional measures might offer. With the tools introduced in  
675 this tutorial, researchers now have the means to analyze their data effectively, uncover patterns, make ac-  
676 curate predictions, and support their findings with robust statistical evidence. By applying these modeling  
677 techniques, researchers can improve the validity and reliability of their studies, ultimately leading to more  
678 informed decisions and advancements in their respective fields.

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